INTRODUCTION

Ever since the recent rise of inequality over four decades ago, social scientists have been preoccupied with the common question as to why income inequality exists. An extensive literature provides exemplary insights into this question. For instance, by now we know that income inequality has been driven by (1) the skill-biased demand and disproportional premium for higher education; (2) erosion of labor market institutions – like the decline of unionization, falling levels of minimum wages and decentralized wage-settings – and (3) changing employment structures (Acemoglu 2002; Autor et al. 2008; Autor 2010; Card and Lemieux 2001; Dinardo et al. 1996; Freeman and Katz 1994; Kim and Sakamoto 2008; Lemieux 2006; Mouw and Kalleberg 2010; Western and Rosenfeld 2011).

Yet, while each of these explanations offers complementary insights about the sources of the *rise* in inequality, they fall short in explaining the forces and mechanisms through which inequality has been *sustained* over time. From a cumulative disadvantage perspective inequality-sustaining processes emerge through critical events that, although temporal in nature, produce systematic and long-term disparities across individuals or groups of people that perpetuate over time (DiPrete and Eirich 2006). Unemployment is considered such a critical event. Especially, with the changing skill demands, vanishing occupations in the middle and the rise of more precarious forms of employment contracts it has become a lived experience in the employment careers of many individuals. The significance of diverging labor market prosperities by employment status in existing explanations suggests that job instability in general, and unemployment in specific, should shape conditions that sustain trends of income inequalities over time. Yet, systematic evidence that links individuals' (un)employment history (in terms of unemployment duration and frequency) with variations in income inequality remains noticeably scarce. There are two main reasons for this scarcity.

First, empirical research that speaks to this gap has focused exclusively on wage differences between groups of workers (DiPrete 1981; Gangl 2004; 2006; Mooi-Reci and Ganzeboom forthcoming). Such a focus has provided a partial view about the magnitude of total income inequalities that – as we know – consist of both between and within-group variations in wages. Wage dispersion within similar groups of workers reflects the variability in employers' ordering and ranking of job applicants where highest ranked workers monopolize better-paid jobs (Kornrich 2009; Reskin 1991). Employers' prejudgments and potential discriminatory hiring practices with regard to workers' (un)employment histories are difficult to measure and have been rarely assessed in relationship to wage inequality. Consequently, our knowledge on within-group wage inequality has remained largely incomplete.

Second, with exception of Mouw and Kalleberg (2010), conventional methods deployed to investigate trends of income inequality have usually relied on cross-sectional data that focus on average earnings variation by occupation (Kim and Sakamoto 2008), education (Autor et al. 1998; Card and Lemieux 2001) or union group (Western and Rosenfeld 2011). While clearly valuable, the use of cross-sectional data misses out wage dynamics that relate to employment status fluctuations or other unobserved individual-level characteristics that change within individuals nested within groups and over time. Fluctuations in employment status influence greatly the evolution of income inequalities, because they can lead to shifts into jobs that invoke greater wage variability. Taking these fluctuations into account is therefore critical to understand forces that perpetuate income inequality.

In this study, we address both of these gaps and offer two extensions to previous research. First, we advance existing theory on income inequality by drawing attention to between- and within employment group inequality, net of individual level differences that influence wage variations in the conditional mean and variance over time. This allows us to compare how previous unemployed workers' changing returns in the observable characteristics together with unobserved ambiguities surrounding their unemployment history (i.e., potential discriminatory practices and prejudgments) relate to variations in income inequality. In doing so, we develop a theoretical argument that predicts that unemployment is important in explaining inequality because it influences *jointly* (a) the relative wage loss *between* groups of workers and (b) the residual wage variability in the order and ranking of job applicants. Testing this hypothesis allows us to add *complementary* within-group and over-time insights into the broader inequality debate, which has been predominantly focused on the sources of the *onset* in rising inequality rather than on the mechanisms through which inequality is *sustained* over time.

Second, our study empirically tests the validity of this hypothesis by focusing on the Dutch labor market that – with its unique supply and demand structure – creates exceptionally diverse employment histories which are key for testing our central hypothesis. We use a comprehensive dataset of the Dutch Labor Force – OSA that spans over the period 1986-2008. OSA is the longest longitudinal dataset in the Netherlands. It provides biennial information on schooling, employment, labor market histories and incomes of all adult members (aged 16 years or over) in the household. The relatively long observation periods, allow us to track labor market histories and trace the evolution of wages as these develop within individuals over time. Using this comprehensive dataset allows us to present an innovative method that extends Western and Bloome's (2009) and Mouw and Kalleberg's (2010) variance function regression to variance function *panel* regression via the (mixed effects) hybrid model presented by Allison (2009). This integrated method allows us to estimate more effectively inequality trends within a panel data setting, thus being able to offer new substantive insights.

Before presenting our analyses, we start with a description of changes in the Dutch labor market that have coincided with a growing trend in income inequality. We then outline the underlying labor market theories and existing literature to portray how unemployment variations relate to trends of income inequality between and within groups of workers. We continue with the presentation of the new variance function panel model that tests predictions from our theoretical model and find that unemployment variation explains a substantial part of the ongoing trends of income inequality.

THE RISE OF INEQUALITY: THE CASE OF THE NETHERLANDS

THE DUTCH PUZZLE OF INCOME INEQUALITY

Income inequality has been largely compressed in the Netherlands compared to other Western societies. Yet, since the mid-1980s its increase has been remarkable. The income inequality as measured by the Gini coefficient rose with 14 percentage points between 1985 and 1990 (Atkinson and Salverda 2005; Salverda et al. 2013) and remained stable during the 1990s (Groot and de Groot 2011). Recent evidence demonstrates that trends of inequality have been much more drastic and dispersed in the Netherlands than already acknowledged in the literature (Salverda et al. 2013). We now know that where the average real incomes of workers in the bottom decile declined 30 percent below the level reached in the 1970s, the incomes of the top deciles grew with 8 percent from 19 to 27 percentage points since the mid-1980s (Salverda et al. 2013). Different from the United States where the rising wage inequality was amplified by a slower growth in the supply of higher skilled labor relative to those of lower skilled (Freeman and Katz 1994), this was not the case in the Netherlands (Freeman and Katz 1994). In fact, studies reveal that in the Netherlands, the increased demand for skilled labor was compensated by an increase in the share of higher educated, which took place over longer periods (Nahuis and de Groot 2003; Groot and de Groot 2011). This means that skewed supply of skilled labor is unlikely related to the Dutch rise in income inequality. Alternative explanations may be related to some major structural changes in the Dutch labor market that took place during the same period of time. The introduction of flexible and part-time employment and a wave of restrictions in the unemployment benefit structure changed the employment structure on a macro-level. On a micro-level these changes led to more heterogeneous careers and more variation in labor market opportunities and career prosperities within and between groups of workers. This breadth of career heterogeneity makes the Dutch labor market unique in its structure to investigate how unemployment dynamics relate to trends in income inequality.

CHANGING SUPPLY AND DEMAND STRUCTURES

The introduction of flexible employment contracts and the creation of part-time jobs have often been regarded as factors that changed considerably the Dutch employment and occupational structure since the 1980s. Between 1985 and 1995 job creation rate averaged 1.8 percent per year in the Netherlands, against 1.4 percent in the United States resulting in the creation of over a million new jobs in ten years times (Visser 1998). Nine out of 10 of these newly created jobs were part-time jobs (i.e., defined as jobs between 12 and 30 working hours). They were highly female dominated and concentrated in the education, health and services sector. The growth in the part-time employment coincided with a shift from a manufacturing-dominated to a services-oriented economy. A consequence of this shift was a drop in the share of employment in the middle paid occupations such as sales, production, craft, repair as well as operators and fabricators that consisted mainly of male workers (Salverda et al. 2008; De Beer 2006). The rise of part-time jobs and flexible employment contracts led to an explosion of female participation rates that went hand-in-hand with growing pay penalties and wider hourly wage inequality (Salverda et a. 2014; Salverda et al. 2008; De Beer 2006). For instance, recent empirical evidence shows that part-time jobs carry a pay penalty of about 3.2 percent and 1.9 percent lower hourly wage for respectively Dutch men and women (Fourage and Muffels 2009). This wage differential grows with the time spent in these jobs, namely: the longer men and women spend in part-time jobs the higher the hourly wage penalty becomes compared to those in full time jobs (Fourage and Muffels 2009). During the same period, the proportion of jobs with fixed-term contracts grew steadily from 8 percent in 1987 to around 15 percent in 2011 (Mooi-Reci and Dekker 2013). This high proportion of fixed-term employment is unique to the Dutch labor market (with exception to Spain; see Casals 2004) and is positively related with recurrent unemployment spells, particularly among men (Mooi-Reci and Dekker 2013).

These structural changes imply that the rise of precarious forms of atypical employment such as part-time and flexible employment contracts and their concentration in sectors that pay less may have contributed to the rise in income inequality. This is through careers becoming more flexible and yet more vulnerable to periods of recurrent unemployment that widen group differences in pay.

Changing Unemployment Benefit Systems

Parallel to the rise of part-time and flexible type of jobs has been a wave of restrictive reforms in the Dutch unemployment insurance benefits. Starting in the mid-1980s, two major reforms (in 1985 and 1987) aimed at shortening the duration and lowering the level of unemployment benefits, followed by another reform in 1995 that restricted the criteria for unemployment entitlement even further (see Mooi-Reci and Mills 2012 for a detailed description of the Dutch reforms). Existing studies on the consequences of income inequality demonstrate a higher level of uncertainty and decrease in social trust when benefit institutions get entrenched (Nannestad 2008; Rhothstein and Uslaner 2005). Similarly, in the Dutch case these transformations portray the shift from one of the most generous unemployment benefit system into one of the most stringent in the world. They also portray the changing normative dynamics and social attitudes about how the Dutch contemplated with issues around access to the unemployment benefit system or the duration of one's unemployment period. The shift towards a more stringent benefit system may have produced a more culturally divided society with stronger "us versus them" rhetoric.

Overall, these structural changes in the Dutch labor market and benefit institutions provide us with the contextual background to understand some major factors that shaped more diverse, flexible and erratic working careers over time. While it is not the scope of this study to test how these structural changes or policy reforms relate to income inequality, we argue that such trends may have shaped conditions that facilitate employment fragmentation and recurrent unemployment over time.

UNEMPLOYMENT AND WAGE INEQUALITY: THEORY AND EXPECTATIONS

Between-Group Inequality: Changing Human Capital and Matching Returns

How does unemployment relate to wage inequality between groups of workers with different employment history? Much of the theoretical considerations for understanding the wage differentials between individuals who differ only with respect to their unemployment histories originate from the traditional (1) human capital and (2) job search theory. The cornerstone of the first is that *general* attained knowledge and *specific* acquired skills through experience are two key human capital resources that play a prominent role in the wage bargaining process (Becker 1964, 1993). Particularly, the higher the level of attained knowledge through education the higher one's individual productivity and the higher the wage returns when valued by the labor markets. Conversely, the set of specific skills that are acquired through on-the-job training and through tenure are usually tied to a specific firm or a specific occupation and result in higher wage returns within the firm in which one is employed. This means that the more specific skills are tied to a specific firm, the less transferable they will be to other organizations. This latter component is particularly important to those experiencing unemployment. It is the depreciation and loss of job specific knowledge through the duration and frequency of earlier unemployment occurrences that determines the magnitude of the current wage loss (Kletzer 1989, 1998). Thus, group differences in wages reflect the change in the returns to workers' job specific knowledge and work experience. In this respect, the cost of unemployment in terms of wage loss can be summarized as the difference between the pre- and post-unemployment wages (Farber 1993) relative to the wage change experienced by those equivalent workers who remained in continuous employment. This wage difference captures the foregone job-specific skills and benefits that vary across workers' individual specific characteristics, such as gender, and vary by the length of unemployment exposure.

Another important mechanism that defines the level of wage differentials is the quality of the job match. A *matching specific* explanation from the job search theory argues that wage differentials between groups arise due to the failure to find a job that matches workers' abilities and previous attained knowledge, skills, and acquired work experience (Lippman and McCall 1976; Mortensen 1977). For instance, having a job that matches the attained education and previous work experience leads to higher job satisfaction, greater productivity, better promotion perspectives and eventually higher wages over time (Wolbers 2011; European Union 2012; Gesthuizen and Dagevos 2008). For a previously unemployed worker, the quality of the job match depends on the available time to screen and the financial resources to sort out a suitable job. Given these constrains, an unemployed worker's optimal strategy is to form a reservation wage which is defined as the minimally acceptable wage offer in the labor market (Mortensen 1977). With the elapsed time in unemployment and with exhausting financial resources, an unemployed worker is more likely to settle for jobs that are either located in different industries, or lower positioned and of poor contract continuation opportunities (i.e., temporary contracts). This means that a poor job match will translate into higher and more persisting wage differentials between groups of workers.

In short, the loss and non-transferability of specific knowledge together with a poor job match are two key explanatory mechanisms that explain why wage differentials exist between groups with and without previous unemployment experiences. These wage differentials aggravate when combined with jobs that do not match with workers' previous attained knowledge and experience. They also aggravate when opportunities to invest in future abilities and skills are limited by contracts with a definite ending date.

Within-Group Inequality: Employers' Preferences and Uncertainty

Wage differentials may also reflect employer's variability in hiring and uncertainty about unemployed workers' future productivity. Screening models (Arrow 1973; Spence 1973), also known as stigma (Eliason 1995) or signaling models, provide some helpful directions for understanding employers' variability. According to the screening theory, hiring decisions are taken under uncertainty about workers' productive capabilities. Because workers' productivity and their fit with the organization is not known beforehand, employers rely on the observable characteristics that signal their future productivity. Such characteristics can be the level of education, gender, and ethnicity, which serve as a screening device in the hiring process (Arrow 1973; Eliason 1995; Spence 1973). Likewise, unemployment histories become an important indicator of workers' future work performance and productivity and hence influence the hiring process. For instance, a single unemployment occurrence may already inflict a negative signal about a worker's future productivity. This negative signal – and the uncertainty that goes with it – amplifies with any repeated or extended periods of unemployment in the past. This means that the longer and the more frequent unemployment in the past, the higher the uncertainty about workers' abilities and future performance will be and thereby the higher the residual wage dispersion.

Queuing theories provide additional insights about employers' preferences when hiring (Reskin 1991). The theory contends that employers rank job applicants into queues, which are largely dictated by employers' prejudgments with regard to workers' future productivity. Highest ranked workers monopolize the most desirable jobs leaving workers at the bottom of the queue with the least desirable jobs (Kornrich 2009). Changes in individuals' human capital and variations in their working careers suggest greater variability in employers' hiring preferences with respect to how they order and rank job applicants with different employment histories. Specifically, workers with uninterrupted careers and relevant work experience will be ranked in the top of the queue receiving jobs with best attributes that pay more, with those previously unemployed located in the bottom of the queue receiving jobs of poorer quality and lower wages. In this study, we advance the main assumption of the queue theory by arguing that employers' hiring preferences and hence wage outcomes will vary greatly *within* groups of workers, contingent upon the frequency and duration of previous (un)employment histories. That is, the longer and more extensive workers' unemployment history, the higher the uncertainty about their future productivity and the higher the wage variability within previously unemployed. A similar process drives the wage variability within the group of continuously employed where prejudgments about productivity by employment tenure and experience produce greater wage variability. This queuing process should explain why wage variability exists and persists within groups of workers over time.

In short, employers' hiring preferences should vary considerably with the intensity of previous unemployment histories. The more frequent and longer the spells of unemployment the higher the ambiguities with regard to workers' future productivity and eventually greater wage variability.

Summary of Theoretical Predictions

The abovementioned theoretical considerations provide the basis for several general expectations. First, if differences in workers' human capital and matching quality induce between-group differences in wages then a *negative* relationship is expected with hourly wages for those in previous unemployment relative to those in continuous employment. At the same time, discrimination stemming from unemployment stigma will lead to significant wage differences between groups of workers. This is because it affects the ranking of job applicants placing previously unemployed workers in the bottom of hiring queues and thereby into lower wage distributions. Second, *within* similar groups of workers wage variability will be guided by employers' prejudgments related to one's unemployment history. Ranking those with less extensive unemployment histories higher on the job queue will induce a *positive* or wider spread of wage inequality within similar groups of workers. Finally, wage differentials and variability between and within groups of workers will exacerbate when interplaying with factors that produce future career fragmentation and repeated unemployment spells, like poor matching qualities and precarious types of employment contracts. Hence, we expect that:

> HYPOTHESIS 1. – *Unemployment variation (e.g., occurrence, frequency –and duration) will have a negative relationship with hourly wages between and a positive relationship with the residual wage dispersion within equivalent groups of workers who differ with respect to their unemployment history, all else equal.*
>
> HYPOTHESIS 2. – *Unemployment in conjunction with job mismatching and temporary employment contracts will exacerbate wage differentials between and wage dispersion within groups of workers who differ with respect to their unemployment history, all else equal.*
>
> HYPOTHESIS 3. – *Unemployment will explain largely the residual wage dispersion, all else equal.*

METHOD, DATA AND MEASURES

METHOD: DECOMPOSING THE WAGE INEQUALITY

Based on the outlined theoretical argumentations, we regard the structure of wage inequality as having two parts: first, a part that is attributed to *between*-group wage differentials that relate to workers' changing observable characteristics given their supply. Second, a part that is attributed to the *within*-group wage differentials with regard to unobservable performance ambiguities and job queue ranking variabilities.

The goal of our model is to decompose these two parts. To do so, our decomposition uses an extension to the variance function regression introduced and discussed by Western and Bloome (2009) and applied in Western and Rosenfeld (2011). In such regression models, the mean and the variance of an outcome depends on independent variables that explain between- and within-group inequality. Following Western and Bloome's (2009, p. 299) formulation and presentation, we model an outcome variable y_i (i=1,…, n) with two submodels: a submodel of the conditional mean, $\hat{y}_i$, and a submodel of the conditional variance, $\log \sigma_i^2$, both as a function of a set of independent variables:

$$\hat{y}_i = \mathbf{x}_i'\boldsymbol{\beta} \qquad (1)$$

$$\log \sigma_i^2 = \mathbf{z}_i'\boldsymbol{\theta} \qquad (2)$$

where $\mathbf{x}_i$ is a K×1 vector of explanatory variables for the mean, $\mathbf{z}_i$ is a J×1 vector of explanatory variables for the variance, and $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are their respective parameter vectors to be estimated. Note that when the outcome variable of (1) is wage or income, it is often transformed by the natural logarithm. In equation (2) the coefficient estimates from equation (1) are used to calculate the logged squared residual that is used as the dependent variable at this stage. The model can be estimated using standard software such as STATA via a maximum likelihood two-stage maximum likelihood estimator by iterating between the linear regression of (1) and the gamma regression of (2), a restricted maximum likelihood estimator that produces less biased estimates in small samples, and a Bayesian estimation (Western and Bloome 2009). Because we have a large sample, we apply the two-stage maximum likelihood estimator. Note that unlike the typical linear regression model of (1) only, the variance function regression of (1) and (2) together relaxes the homoscedasticity assumption of the usual linear regression because the residual variance is allowed to vary with covariates (Western and Bloome 2009). Therefore, the analyst can model heteroscedasticity in the data directly via the inclusion of covariates. As in a typical bivariate regression model with two dependent variables, the mean and the variance of y_i are assumed to be independent, conditional on their respective covariates, and, unless specified differently, the mean and the variance of y_i are assumed to be linear functions of the covariates.

The variance function regression model specified in (1) and (2) is valuable to decompose between and within *group* variations in wages. Yet, at this stage, it does not allow to control for individual-level differences nested within employment status groups and over time. Another issue is that in our study we rely on panel data where serial correlation over time is present and remains uncontrolled for in variation function regression models. As hypothesis 1 suggested, unemployment variation in one's employment career can influence greatly wage dispersion between and within groups of individuals respectively due to (1) foregone education, job specific knowledge and mismatching and (2) employers' hiring perceptions with regard to one's future productivity. To capture this simultaneous effect of unemployment, net of (un)observed individual level differences, we propose the integration of the variance regression of (1) and (2) with Allison's (2009) hybrid model. The hybrid model decomposes each time-varying covariate into a within-person components (e.g., which is the deviation from that individual-specific mean) and a between-person component (e.g., which is the mean of each individual-specific variable). To combine these two models, we engage in a two-step estimation algorithm.

In the first step, we measure the between-group wage inequality by estimating the variance in the conditional means $\sum_i^N w_i\,(y_i - \bar{y})^2$, where, w_i is the sample weight for respondent i and $\bar{y}$ is the grand mean of log hourly wages. This provides us with the $\boldsymbol{\beta}$ regression coefficient vectors for between-group inequality as this develops over time and across groups of workers with and without unemployment experiences. The decomposition of the mean is based upon a regression of the log hourly wage y for individual i at time t written as follows:

$$\hat{y}_{it} = \mathbf{x}'_{1i}\boldsymbol{\beta}_1 + \bar{\mathbf{x}}'_{2i}\boldsymbol{\beta}_2 + (\mathbf{x}_{2it} - \bar{\mathbf{x}}_{2i})'\boldsymbol{\beta}_3 + \bar{\boldsymbol{u}}_i\alpha_1 + (\boldsymbol{u}_{it} - \bar{\boldsymbol{u}}_i)\alpha_2 \quad (3)$$

where, $\mathbf{x}_{1i}$ is a $K_1 \times 1$ vector of time-invariant variables (such as gender, survey year), $\bar{\mathbf{x}}_{2i}$ is a $K_2 \times 1$ vector of the person-specific means of time-varying covariates (such as age, education at interview date, sector, marital status, home living children, occupational status and mismatching indicators), $(\mathbf{x}_{2it} - \bar{\mathbf{x}}_{2i})$ is a $K_3 \times 1$ vector of deviations from the respective person-specific means of the same time-varying covariates. The $\boldsymbol{\beta}$s in submodel (3) contain their respective vectors of parameter estimates for between-group wage inequality that are captured in the respective vectors $\boldsymbol{x}$. The vector ($\boldsymbol{u}_{it}$) includes three unemployment indicators (i.e., whether or not ever unemployed; the frequency of unemployment, and the duration of unemployment spells over the observation period) with α_1 denoting the fixed effect of the three unemployment indicators and α_2 denoting the *effect* of deviations from the mean of time-varying unemployment indicators. This step produces a set of estimates that tell us how much each unemployment indicator contributes to the between-group wage inequality, net of individual-level and matching differences.

In the second step, we use the coefficient estimates and unemployment effects from the first step to calculate the squared residual σ_i^2 for each case by using a sample weight as proposed by Western and Bloome (2009). We do this because the standard errors would be incorrect otherwise; we ignore heteroscedasticity in y_i. We use the log of this squared residual as the dependent variable for our model of conditional variance that is written as follows:

$$\log\sigma_{it}^2 = \mathbf{z}_{1i}'\boldsymbol{\theta}_1 + \bar{\mathbf{z}}_{2i}'\boldsymbol{\theta}_2 + (\mathbf{z}_{2it} - \bar{\mathbf{z}}_{2i})'\boldsymbol{\theta}_3 + \bar{\boldsymbol{u}}_i\alpha_1 + (\boldsymbol{u}_{it} - \bar{\boldsymbol{u}}_i)\alpha_2 \quad (4)$$

The notation of the variance panel regression submodel (4) follows that of (3). Here, the $\boldsymbol{\theta}$s represent the effects on the residual variance from (3) that are captured in vector $\boldsymbol{z}$. Equations (3) and (4) jointly specify a variance function panel regression model that is estimated using the two-stage maximum likelihood estimator. In the context of our study, this step estimates how much each of the unemployment indicators contribute in the conditional wage dispersion, controlling for individual level and matching differences. The advantage of this integrated model is that it estimates a model that analyzes both the heteroscedasticity and the serial correlation in the data at the same time. This is achieved by including the mean of all covariates, the deviation of these covariates from their respective within-person means, and a dummy for each panel year. In addition, it also allows us to estimate time-constant variables that would not have been possible in conventional fixed effect models. Similar to the traditional decomposition models, the mean and variance submodels are estimated separately.

As hypothesis 2 suggested, previous unemployment exacerbates wage differentials between and dispersion within groups of workers when previously unemployed end up in jobs that do not fit with their previous knowledge and experience; or when they take up jobs with a definite end date (e.g., temporary employment contracts). To capture this moderating effect, we introduce five interaction terms between the variable ever unemployment and (1) mismatched jobs, (2) overeducated, (3) undereducated, (4) differently educated and (5) type of employment contract.

Finally, our third hypothesis suggested a strong association between unemployment and wage dispersion. To measure how much of the increase in wage inequality is explained by unemployment, we follow the approach as proposed by Western and Rosenfeld (2011) and proceed as follows. We calculate the level of wage inequality by assuming that the risk of individual *i* to experience unemployment remains at its initial level of 1986. We retain the level of 1986 by reweighting the data to preserve the initial level of unemployment within individuals across all years from 1986 to 2008. We then use the adjusted weights to adjust the variances across the years by fixing the share of jobs with temporary employment contracts and the rate of job mismatching at the respective levels of 1986.

DATA

We use the longitudinal data from the Dutch Labor Supply Panel OSA for analyzing the link between unemployment and wage inequality. The OSA panel study is targeted at a representative sample of 4,000 to 5,000 respondents in each wave, first drawn in 1985 and then in 1986 with further biannual waves until 2000 (Abbring 2002; NIWI 2000). For this study we use the data from 1986 and onwards. The survey has good measures of respondent's family background, education, and incomes. Moreover, the data provide detailed information about respondents' labor market situations with start and ending dates of unemployment episodes, making it possible to track and trace transitions in a dynamic way. To study wage inequality, the analyses are restricted to workers between 21-64 years old who had been previously employed for at least some periods of time by the time of interview. Our data counts 38,810 repeated wage observations across 15,284 workers over the period 1986 to 2008. From these, 33,037 wage observations were spread across 13,174 workers who were observed in continuous employment during the observation period. The remaining 5,773 wage observations were distributed across 2,110 respondents who were unemployed at some point during the observation period (see for the descriptive characteristics Table 1A of Appendix A). Figure 1A and 1B depict the evolution of employment (1A) and unemployment rates (1B) across men and women in our sample over the period 1986-2008. As shown in Figure 1A, the share of women participating in the labor market increased about 30 percent, from 42 percent in 1986 to 72 percent in 2008. In addition to the increasing trends of employed men and women during our observation period (1986-2008), Figure 1B depicts the share of men and women who experienced unemployment at the interview dates. As expected, the share of the unemployed is higher among women than men, and fluctuates with the economic periods. It is important to note that both the employment and unemployment rates in our OSA sample follow closely the national trends of labor force participation over these years in the Netherlands (OECD 2012).

INSERT FIGURE 1A & 1B ABOUT HERE

MEASURES

Logged hourly wages. The dependent variable in this study is the natural logarithm of hourly wages at time *t* for individual's *i* current job, excluding overtime pay and overtime hours. This is constructed by dividing the monthly net wage by the monthly working hours and then taking the natural logarithm. The dependent variable is deflated by the ratio of mean wages earned in 1986 and only contractual hours are used.

Unemployment. For our study, we use information on the labor force status at the time of interview and in-between interviews. The advantage of the OSA panel data is that it records retrospective information about the change of the labor force status. From this information, we can derive whether additional unemployment spells have occurred in between two interview dates. Using the information, we construct a time-dependent dummy variable recording the status of *ever unemployment*, which takes the value of 1 if the worker has been ever unemployed at the time of interview or in-between interview dates and 0 if the respondent has been continuously employed over the observation period. Consistent with the theoretical arguments, we include also two additional unemployment indicators. The first is a count variable for *unemployment frequency* of person *i* during the observation period *t* distinguishing between 1, 2, 3 and 4+ spells of unemployment with 0 those in continuous employment. The second additional variable is the *duration of unemployment* (in months), which is defined as the difference between the end and the start date of unemployment that occurred between two interview dates. Those reporting durations lower than a month are recoded as 0.5 while the reference category of 0 consists of those in continuous employment. Consistent with the theory we expect each of these three unemployment indicators to have a *negative* relationship with hourly wage outcomes and a *positive* relationship with the residual wage dispersion.

Measures of subjective mismatch. We construct two measures that capture the type of mismatching. First, we construct a variable of (subjective) *job mismatch* indicating whether a worker's current employment is outside one's discipline (1= if "yes" and 0 if "no"). Second, we create a set of dummy variables indicating the match between the required education on the current job and the acquired education of the worker. The first dummy variable *overeducated* takes the value of 1 if the worker is more highly educated than required in the present job, 0 otherwise. The second dummy variable of *undereducated* takes the value of 1 if the worker is lower educated than required in the current employment with 0 otherwise. A third dummy variable for *differently educated* takes the value of 1 if the worker has a different education than required on the current job. Finally, the dummy variable *outdated* takes the value of 1 if the education and knowledge pertaining to the current employment is outdated, 0 otherwise. Consistent with our theoretical predictions, we expect that unemployment in conjunction with the different forms of mismatching will have an *exacerbating negative* relationship with hourly wages and an *exacerbating positive* relationship with the residual wage dispersion.

Type of employment contract. Another principal variable for exacerbating between- and within-group wage inequality is the type of employment contract at the time of interview (0= permanent/regular contract, 1= temporary employment contract). Temporary employment contract is defined as employment with a fixed termination date, with those continuing employment contracts as the reference category. Also here the interplay between unemployment and temporary employment contracts will lead to a negative exacerbating relationship with hourly wages and wider (positive) wage dispersion.

Human capital variables. To capture the wage gains stemming from human capital resources, three variables are used. First, the variable *education* measures individuals' attained level of education. We create three dummy variables for education levels, distinguishing between three categories: (1) elementary education, which indicates the completion of elementary school (in the Dutch system, BO); (2) intermediate education, which indicates the completion of lower and/or upper intermediate secondary school (in the Dutch system, LBO-MAVO-VMBO-HAVO-VWO-MBO); and (3) college/university education which indicates the completion of a college or university degree (in the Dutch system, HBO-WO). Second, the variable *age* ranging between 21-64 years is used as a proxy for worker's employment experience and an *age squared* variable to capture any non-linearity's in our observations. Finally, the variable *employment tenure* measures the length of employment periods during the observation period in our data, constructed as the difference in the months between the end and the start of the most recent employment spell.

Job characteristics and demographic variables. We also acknowledge that differences in job characteristics and family situation may drive wage differentials. We have therefore constructed the following variables. A dummy variable for *sector* was created (0 = private; 1 = public sector); *industry* (distinguishing between 11 different industries: governmental services; education services; professional services; business services; durable and non-durable manufacturing and mining; transportation; construction; retail trade and grocery, whole trade, repair services; agriculture; forestry; fisheries). We also construct a variable for the *level of occupational status* at the time of interview using the International Socio-Economic Index (ISEI) scale of Ganzeboom et al. (1992). To control for pay differences due to demographic characteristics, we also include *marital status* (1 = married/cohabiting; 0 otherwise), and *home living children* (1 = no; 2 = 1+ home living children). Because theoretically we expect men and women to differ in their labor market experience and to have different labor market behaviors, we have conducted the analyses for men and women separately.

Employers' prejudgments and potential discriminatory practices. These are measured by estimating the residual variance σ_i^2 for each sample of respondent i with corrected standard errors (see previous section). Here, negative characteristics like unemployment occurrence, duration and frequency should be positively related with residual wage disparities. Similarly, positive characteristics like education, experience, tenure and high status jobs should be negatively related with residual wage disparities.

RESULTS

UNEMPLOYMENT, UNCERTAINTY AND WAGE INEQUALITY

Using equation (1) and (2) we plot Figure 2A and 2B respectively. The first depicts the evolution in the mean (e.g., between-group), while the second plots the evolution in the variance of wages (e.g., within-group) over the period 1986-2008 *before* controlling for individual level differences. The key finding from the Figures 2A and 2B is that they show a clear correlation between the growing wage gap in the mean and the growing gap in the variance of log of hourly wages of workers who differ with respect to their employment status. Specifically, while for the continuously employed the mean of log hourly wages remains fairly constant since the mid-1980s that of previously unemployed drops remarkably from 1990s. It is obvious that this trend has gone hand-in-hand with a trend of growing wage dispersion amongst the group of previously unemployed (see Figure 2B) since the 1990s.

INSERT FIGURE 2A and 2B ABOUT HERE

We now turn to the extended models where we consider two complementary explanations for the growing wage inequality. Following arguments from the human capital and matching theories, wage inequality grows due to differences in the knowledge and experience of workers who differ with regard to their employment histories. In addition, the residual wage explanation argues that the unexplained component of wage inequality increases due to ambiguities and uncertainties that surround employers' decisions when hiring previously unemployed. As suggested in our first hypothesis, these explanations suggest that unemployment variation (e.g., in the occurrence, frequency –and duration) will have a negative relationship with hourly wages between; and a positive relationship with the residual wage dispersion within equivalent groups of workers who differ with respect to their unemployment history, all else equal. To test these effects simultaneously, we *jointly* estimate between- and within-group differences in Table 1A (for men) and 1B (for women). The separate gender models allow us to estimate the specific gender wage gap and dispersion by employment status. The β columns (i.e., Models 1 and 3) in Table 1A and 1B show (partial) estimates from our variance function panel models among workers with different employment histories and net of differences in marital status, occupational level, and survey year (full estimations are available upon request). Substantively, the βs describe how variations in workers' observable characteristics influence the development of log hourly wages within workers of a specific group (i.e., with or without unemployment) over time.

INSERT TABLE 1A ABOUT HERE

Using a one-tailed test for our first hypothesis, results in the β column from the baseline Model 1 in Table 1A indicate that ever unemployed men earn about 13 percent lower hourly wages compared to those in continuous employment. In addition, they suffer a four percent wage loss for every 10 additional months in unemployment and a six percent wage penalty for any additional unemployment spell. Interestingly, results from the θ columns from the baseline Model 2 show that for the ever unemployed men there is higher wage dispersion with about 0.551 variance units on the average. This dispersion tends to increase with 0.15 units for every 10 additional months in unemployment while this does not hold for any additional unemployment frequencies. When we control for individual differences and the role of mismatching in the β column from the full Model 2, wage differences related to the duration and the frequency of unemployment spells largely disappear. What remains is the wage differential associated with ever unemployment, which is about 5% ($\beta = 0.049$; $p < 0.10$, one-tailed test). In addition to wage differentials, results from the θ column in Model 4 indicate that the residual wage dispersion that is coupled with ever unemployment and unemployment duration remains substantially evident after controlling for the necessary variables. Specifically, wage inequality widens with about 0.492 units for ever unemployed men and with 0.28 units for every 10 additional months in unemployment.

Results in Table 1B repeat the decomposition analyses for women. Using a one-tailed test, results from the β column in the baseline Model 1 indicates a wage differential of about 15.8% for women who were ever unemployed and an additional 4% that comes with every additional 10 months in unemployment. Interestingly, results from the θ column of the baseline Model 2 suggest virtually no residual wage dispersions associated with any unemployment indicator among women. When we control for individual differences and job mismatching in the full Model 2, initial wage differences become smaller in size and weaker in significance. Similar to men, women suffer from a wage penalty that relates to the type of employment contracts. Specifically, the wage penalty for a job with a temporary employment contract is largely significant and about 4.5% among women. Results from the θ column indicate that temporary employment contracts are associated with a substantial high residual variance in the hourly wages among women. Specifically, having a job with a temporary employment contract increases wage dispersion about 0.404 units.

In sum, these results generally support our first hypothesis by showing that previously unemployed men and women suffer higher wage penalties compared to equivalent workers who remained in continuous employment. Our results reveal that men who were ever unemployed and spent several months in unemployment, experience substantial higher earnings variability (i.e., high residual variance) compared to equivalent men in continuous employment. Such evidence was not found among women, indicating that men are likely to suffer more from unemployment stigma compared to women. This finding lends support to recent evidence from Mooi-Reci and Ganzeboom (forthcoming) that finds that, at least in the

Netherlands, wage penalties for women are due to human capital depreciation while for men these are mainly the product of stigma.

Exacerbating Wage Inequality?

To test our second hypothesis that unemployment will exacerbate wage differentials between and within similar groups of workers contingent upon job mismatching and type of employment contracts, we introduce five interaction terms in Table 2. Using a one-tailed test, results from the β column in Model 1 reveal that amongst men wage differentials between groups of workers exacerbate with the level of undereducation and employment contracts while leaving residual wage dispersion unaffected. Specifically, all else equal, previously unemployed men who believe to be *undereducated* in their current jobs, earn 11% lower hourly wages [–0.048 + (–0.062)= –0.11] compared to those similar undereducated men in continuous employment. Similarly, previously unemployed men in jobs with a temporary employment contract earn about 8.6% lower hourly wages [–0.048 +(–0.038)= –0.086] compared to those with similar employment contracts but with no previous unemployment experiences. Non-significant interaction effects from the θ column in Model 2 indicate that the observed wage penalty for previous unemployment *and* for utilizing jobs with temporary employment contracts in Model 1 is not coupled with an increase in the residual wage dispersion.

Results from Models 3 and 4 for women show a different story. Specifically, using a one-tailed test, results from the β column in Model 3 indicate that previously unemployed women who believe to be *overeducated* in their current job earn about 11.6% lower wages per hour [–0.054+(–0.062)= –0.116] compared to women with a similar level of overeducation who remained in employment. Finally, the wage penalty for previously unemployed women in jobs with a temporary employment contract comes with an *additional* 17.6% wage penalty (above and beyond the main effect for ever unemployment of –0.054) compared to those with similar employment contracts who remained in employment. In contrast to men, results in Model 4 indicate that the moderating effects of mismatching (related to job and overeducation as well the type of employment contracts are coupled with greater variation in the conditional variance and thus wider residual wage dispersion. That is, wage variability exacerbates among previously unemployed women when they accept a job that does not match with their acquired education, or for which they are overeducated or when they are employed in jobs with a temporary employment contract. Overall, these results indicate that, for women, the between – and within group wage variability is contingent upon the type of mismatching and the type of their current employment contract.

INSERT TABLE 2 ABOUT HERE

HOW MUCH DOES UNEMPLOYMENT MATTER FOR INEQUALITY?

To assess how much of the wage inequality is explained by individuals' unemployment history we obtain adjusted variances by fixing individuals' risks of experiencing unemployment at their 1986 levels. This is done by holding constant the effects of workers with temporary employment contracts (versus fulltime), job mismatching, and educational attainment at their levels of 1986. The adjusted within-group variances of log hourly wages are plotted against corresponding observed variances by year, sex, and whether someone was continuously employed (Figures 3 and 4). If workers' unemployment history explains the increasing trends of wage disparity, than the observed and adjusted variance curves in the plots should lie far apart from each other and otherwise.

INSERT FIGURES 3 & 4 ABOUT HERE

Figure 3 demonstrates that, averaged over the period 1986–2008, unemployment occurrence accounts for almost half of the rise in wage inequality among men, net of differences in mismatching, type of employment contracts and education. Specifically, for the period between 1986-2000, unemployment explains about 9 out of the 15 percent of the within-group inequality or almost two-third of the rise in wage inequality among the previously unemployed men. Although for the post–2000 period unemployment starts to lose some predictive power, it still explains almost half of the growth in wage inequality.

For women, Figure 4 illustrates that among those ever unemployed, the observed dispersion of wages started to rise since 1990 and thus, much earlier than for the ever unemployed men. Similar to the effect of their male counterpart, the adjustment again leads to a reduction of the within-group wage dispersion among the previously unemployed and continuously employed women. Specifically, averaged over the period 1986–2008, unemployment occurrence controlled for job mismatching, education and the type of employment contracts explains about 10 out of 16 percent of within–group wage inequality. This indicates that these predictors account for almost two third of the rise in wage inequality among previously unemployed women. Overall, these results lend support to our third hypothesis by showing that unemployment explains largely the residual wage dispersion.

DISCUSSION AND CONCLUSIONS

The goal of this study was to investigate whether and how unemployment (in terms of unemployment occurrence, duration and frequency) relate to trends of wage inequality. We were guided by the central tenet that unemployment shapes the conditions that facilitate trends of wage inequality by influencing *jointly* (a) the relative wage difference *between* groups of workers as well as (b) the residual wage variability *within* similar groups of workers who differ with respect to their unemployment dynamics. This allowed us to compare how previous unemployed workers' changing returns in the observable characteristics and the ambiguities related with respect to their unemployment history (i.e., potential discriminatory practices) relate to trends of income inequality. We focused on the Dutch case because it provided us with sufficient variation in individuals' working careers. This was facilitated through the changing supply and demand labor structures that shaped more diverse and flexible working careers, creating an ideal case study. We combined human capital and job search theories with signaling and job queue theories to develop hypotheses about the underlying process in the between and within-group wage variations. To test the validity of our hypotheses, we integrated the variance function regression models with the Hybrid model to develop a variance function panel regression model for panel data. We applied this integrated model on the OSA data with longitudinal observations among a sample of Dutch workers with observations over the period 1986 to 2008. Adopting a decomposition technique used by Western and Rosenfeld (2011), we partitioned wage inequality into a part attributed to the changes in the returns of individual worker characteristics and the residual part of wage inequality attributed to unobservable performance ambiguities.

Our results demonstrate three central findings. First, we find consistent evidence showing a wage penalty *between* ever unemployed men and women relative to those with no such unemployment experience. So far, this first finding lends support to existing research on unemployment scarring that finds profound wage gaps between groups of workers with different employment histories (Gangl 2004; 2006; DiPrete 1981; Mooi-Reci and Ganzeboom forthcoming). Second, beyond this wage penalty, we find strong variations in the conditional variance in particular *within* the group of previously unemployed men who differ with respect to their previous unemployment duration. For women, residual wage variability is conditional on the type of mismatching (i.e., overeducation, mismatch) and type of their current employment contract. Third, and finally, we find that unemployment has accounted for a substantial part of the rise in wage inequality since 1986. Specifically, over the period 1986-2008, unemployment accounted for about two third of the rise in wage disparity among women and about a half of the rise among men.

Our findings show something ignored in most inequality studies, namely the importance of linking unemployment with trends of wage inequality. Specifically, we showed that while wage disparities among previously unemployed men relate *directly* to employers' prejudgments with regard to unemployment those of women are contingent upon the type of mismatching and their employment contract. What we also learn from these findings is that hiring preferences and discrimination – that is captured through within-group wage variation – have become an important determinant for wage inequality. The potential hiring discrimination that we capture likely interplays with and resonates culture-based gendered believes about the role of men and women in the workforce. For instance, employers' views about the central role of men's employment may negatively overstate ambiguities related to unemployed workers' future productivity that feed wage dispersion. As shown, men whose careers are broken by unemployment are most likely penalized and discriminated in the their wages relative to those with no unemployment and relative to their previously unemployed peers with incidental unemployment. Contrary, negative prejudgments about women's future productivity are conditional and activated with overeducation and temporary employment contracts because they reinforce pre-existing expectations about women's potential career fragmentation. Specifically, women who "choose" for jobs in which they are overqualified or for jobs with a fixed termination date may seem to prioritize their (potential) motherhood role. A role that in employers' eyes may be related to a lower ambition level, higher likelihood of unemployment re-occurrence and should thereby result into lower wages. In this respect, our study has contributed to the ongoing debate on gendered hiring discrimination (Budig and England 2001; Budig and Hodges 2010; Correll et al. 2007; England 2005; Reskin 1991) by showing how employer's prejudgments can induce greater wage variability and lead to group differences in pay.

Our findings offer some implications for future policymaking. For instance, considering the mildly significant positive within-component of the mismatch variable for both the ever unemployed men and women, we suggest a public program helping workers find jobs that provide a good match for their skills, especially those who bear the stigma of having been unemployed. In addition, while for women without such stigma the possession of a higher education degree tends to increase their earning potentials (thus wage inequality between individuals), higher education actually tends to decrease such inequality for the same individuals over time. Therefore, expansion of higher education should be encouraged in the longer run when more women are engaged in continuous employment.

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FIGURE 1A
Labor Force Participation, by Gender, between 1986-2008

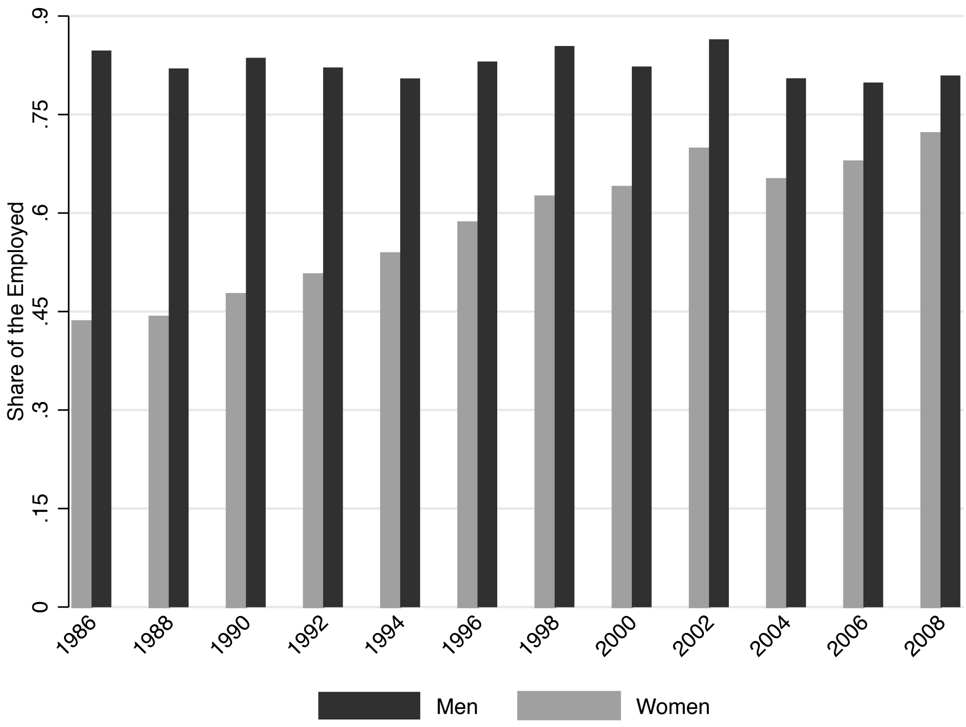

FIGURE 1B
The %-ge Unemployment Rates by Gender, between 1986-2008

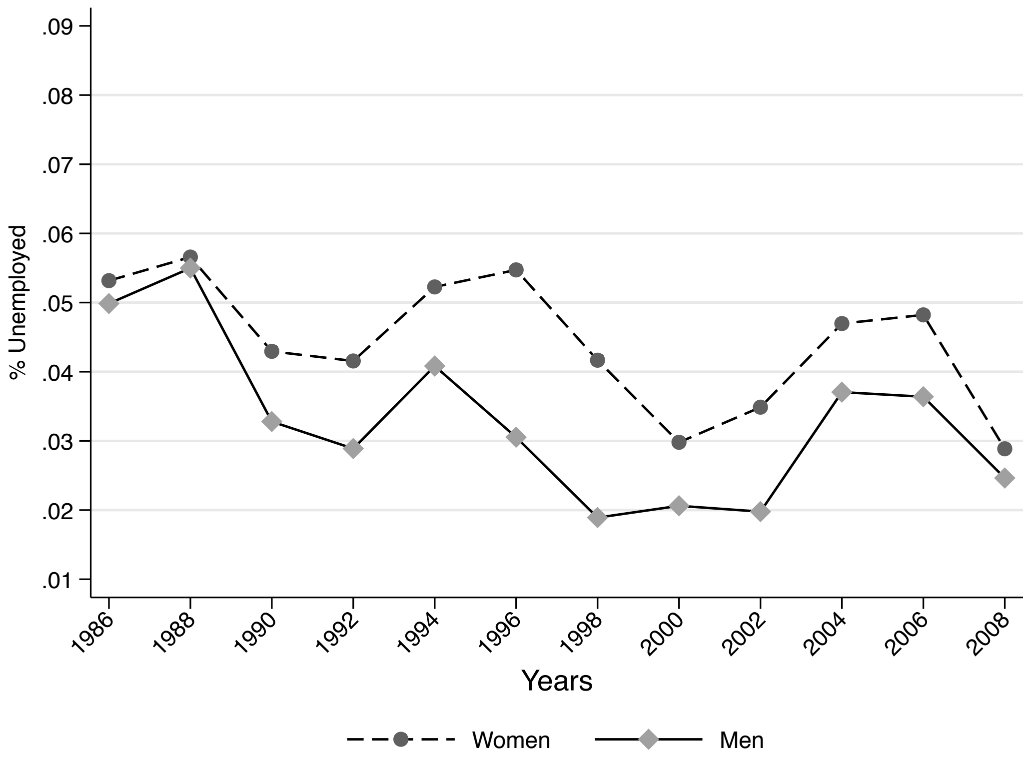

FIGURE 2A
The Mean of Log Hourly Wages, by Employment Status, 1986-2008

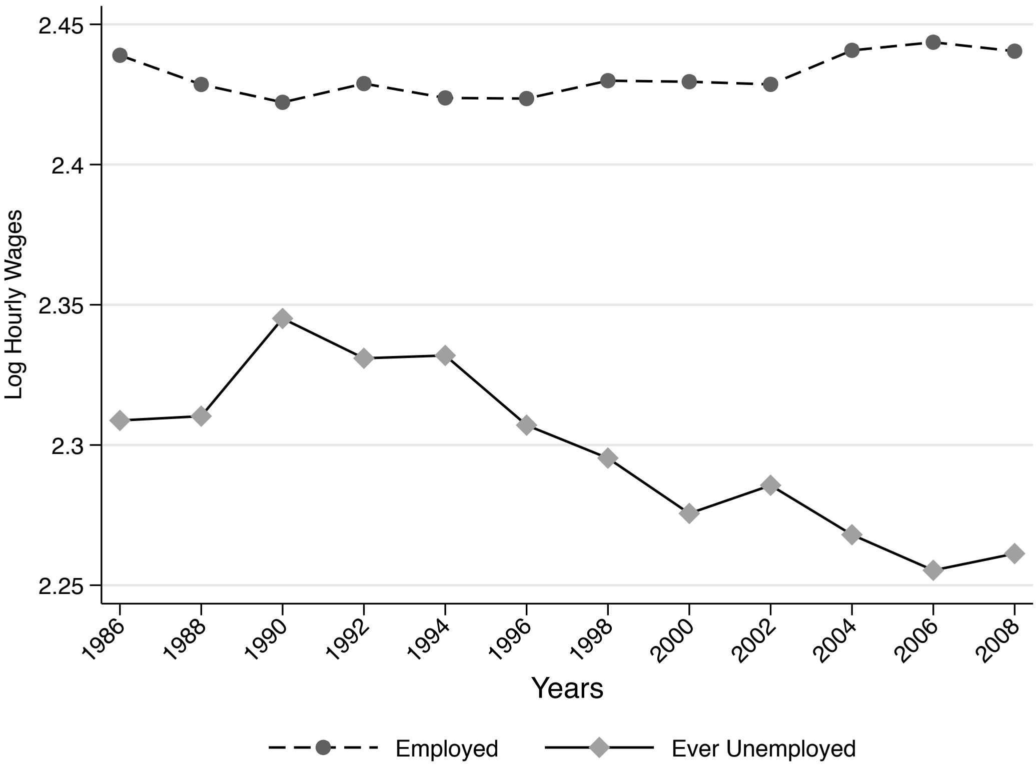

FIGURE 2B
The Variation in Log Hourly Wages, by Employment Status, 1986-2008

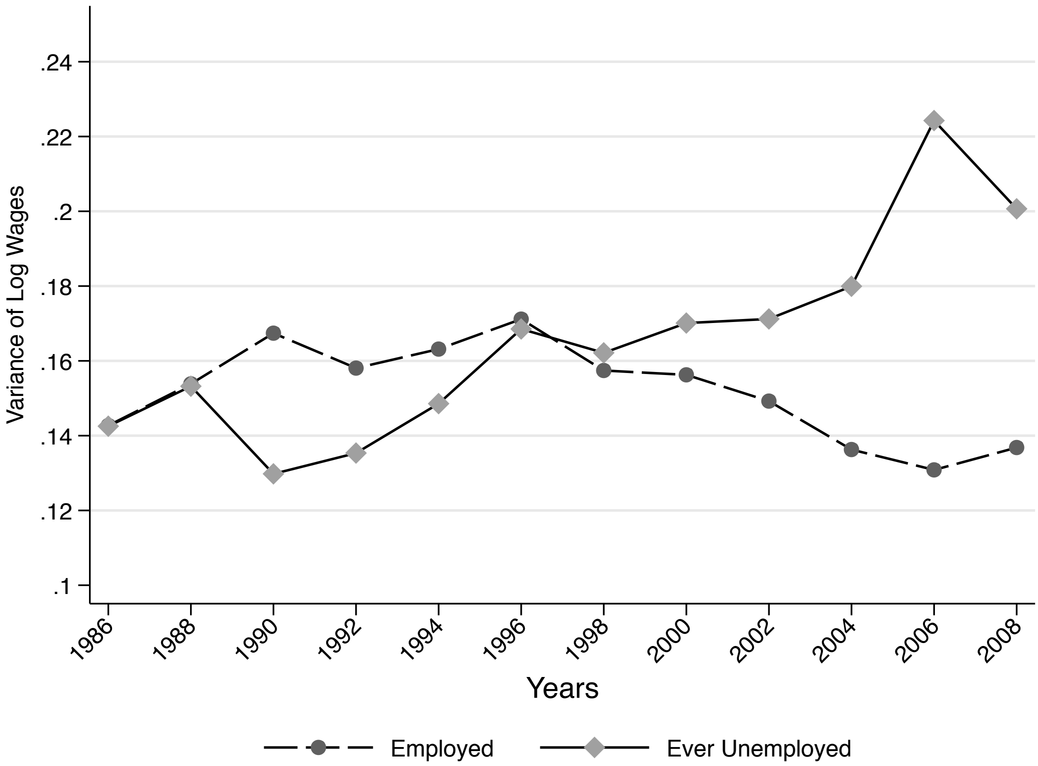

FIGURE 3
Observed and Adjusted Variances in Log Hourly Wages, by Employment Status for MEN only, 1986-2008

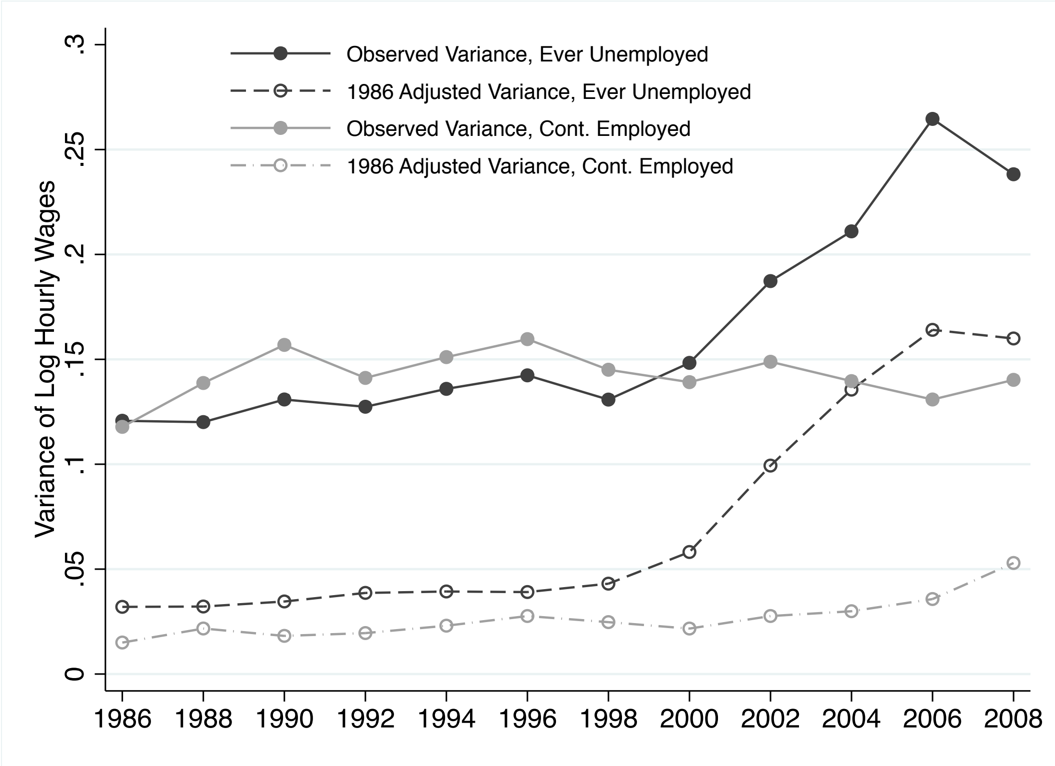

FIGURE 4
Observed and Adjusted Variances in Log Hourly Wages, by Employment Status for WOMEN only, 1986-2008

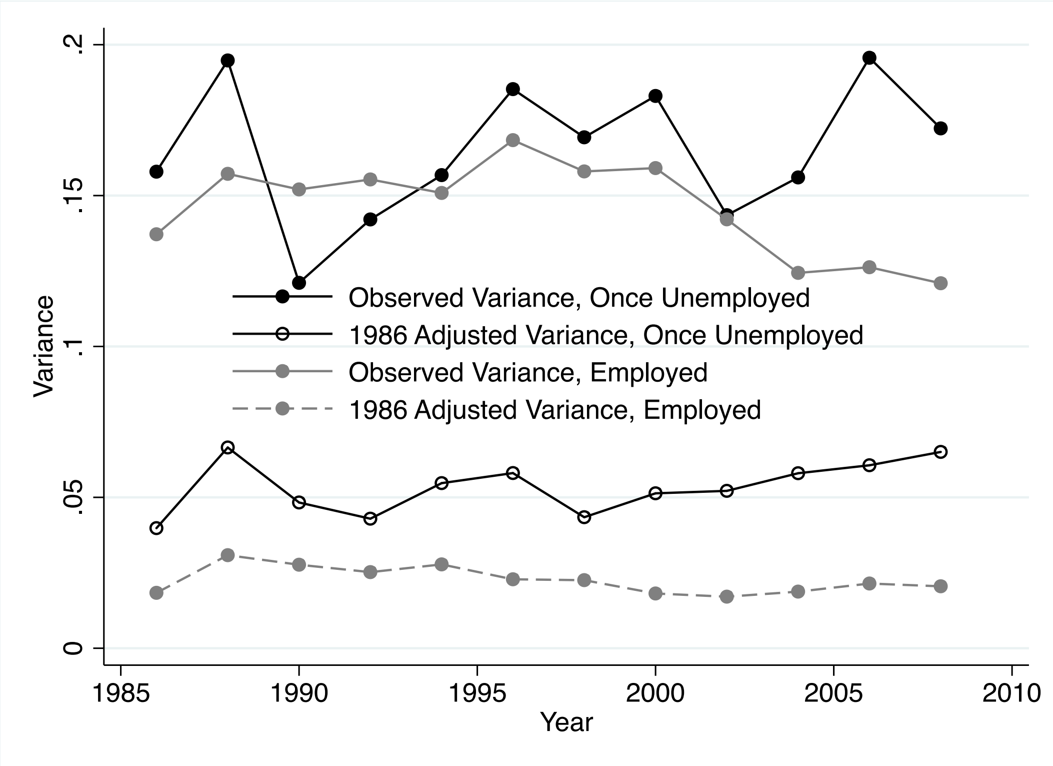

TABLE 1A
(PARTIAL) BETWEEN –AND WITHIN GROUP ESTIMATES FOR MEN

	BASE MODEL				FULL MODEL			
	MODEL 1 *(β)*		**MODEL 2** *(θ)*		**MODEL 3** *(β)*		**MODEL 4** (*θ*)	
	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
Ever Unemployed………………………	-0.132***	(0.000)	0.551**	(0.036)	-0.049*	(0.067)	0.492*	(0.099)
Duration of unemployment (in months)...	-0.004**	(0.025)	0.015*	(0.085)	-0.000	(0.334)	0.028**	(0.016)
Unemployment frequency……...............	-0.060*	(0.063)	-0.631	(0.283)	-0.003	(0.462)	-0.666	(0.237)
Mismatched job…………………………					-0.052	(0.250)	0.102*	(0.080)
Overeducated[a]…………………………...					-0.027***	(0.006)	-0.037	(0.358)
Undereducated[a]…………………………					0.003	(0.427)	-0.061	(0.347)
Differently educated[a]……………………					-0.001	(0.469)	0.097	(0.183)
Employment contract[b] (=temporary) …..					-0.057***	(0.000)	0.510***	(0.000)
Constant…………………………………	2.498***	(0.000)	-1.911***	(0.000)	0.938***	(0.000)	0.619***	(0.008)
Log Likelihood…………………………..	-9,414		-6,562.1		-1,123.2		30,443.3	
Chi²…………………………………...	248.6		97.91		14,141.7		821.5	

NOTE 1. ─ The dependent variable in sub-models (1) and (3) is the log of hourly wages, while in sub-models (2) and (4) the dependent variable is the squared residual. Model 3 and Model 4 also control for the effects of additional covariates including education level, sector, marital status, occupational level, survey year as well as all time-varying covariates at their grand mean level (i.e., averaged over all periods).

NOTE 2. ─ a = Outdated education is the reference category; b = Permanent contract is the reference category;

NOTE 3. ─ *p < .01; ** p < .05; * p < .1 (one-tailed tests).*

TABLE 1B
(PARTIAL) BETWEEN –AND WITHIN GROUP ESTIMATES FOR WOMEN

	BASE MODEL				FULL MODEL			
	MODEL 1 *(β)*		**MODEL 2** *(θ)*		**MODEL 3** *(β)*		**MODEL 4** *(θ)*	
	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
Ever Unemployed………………………	-0.158***	(0.005)	-0.124	(0.372)	-0.090*	(0.053)	0.127	(0.379)
Duration of unemployment (in months)...	-0.004***	(0.009)	0.001	(0.236)	-0.002*	(0.092)	0.013	(0.116)
Unemployment frequency……...............	0.057	(0.152)	0.029	(0.463)	0.005	(0.130)	-0.260	(0.225)
Mismatched job………………………					-0.015	(0.109)	0.032	(0.357)
Overeducated[a]…………………………..					-0.011	(0.206)	0.001	(0.495)
Undereducated[a]…………………………					0.017	(0.232)	-0.025	(0.448)
Differently educated[a]……………………					-0.002	(0.459)	0.146	(0.123)
Employment contract[b] (=temporary) …..					-0.045***	(0.001)	0.404***	(0.000)
Constant…………………………………	2.336***	(0.000)	-1.747***	(0.000)	0.901***	(0.000)	0.174***	(0.000)
Log Likelihood…………………………..	18,525.3		10,504.9		-1,868		16,558.4	
Chi²……………………………………....	6.717		0.659		6704.4		738.9	

NOTE 1. ─ The dependent variable in sub-models (1) and (3) is the log of hourly wages, while in sub-models (2) and (4) the dependent variable is the squared residual. Model 3 and Model 4 also control for the effects of additional covariates including education level, sector, marital status, occupational level, survey year as well as all time-varying covariates at their grand mean level (i.e., averaged over all periods).

NOTE 2. ─ a = Outdated education is the reference category; b = Permanent contract is the reference category;

NOTE 3. ─ $p < .01$; ** $p < .05$; * $p < .1$ (one-tailed tests).

TABLE 2

(PARTIAL) BETWEEN AND WITHIN-GROUP ESTIMATES FOR MEN AND WOMEN, FROM THE INTERACTION MODEL

	MEN				WOMEN			
	MODEL 1 *(β)*		MODEL 2 *(θ)*		MODEL 3 *(β)*		MODEL 4 *(θ)*	
	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
MAIN EFFECTS								
Ever Unemployed…………………………	-0.048***	(0.000)	0.067*	(0.099)	-0.054***	(0.000)	0.036	(0.219)
Mismatched job………………………...	-0.005	(0.227)	0.080	(0.139)	-0.009	(0.218)	0.004	(0.481)
Overeducated[a]……………………………	-0.024**	(0.013)	-0.039	(0.355)	-0.000	(0.497)	-0.036	(0.366)
Undereducated[a]……………………………	-0.000	(0.498)	-0.032	(0.425)	0.014	(0.274)	-0.013	(0.472)
Differently educated[a]……………………..	-0.004	(0.356)	0.098	(0.381)	0.002	(0.449)	0.099	(0.220)
Employment contract[b] (=temporary) …….	-0.060***	(0.000)	0.506***	(0.000)	-0.050***	(0.000)	0.422***	(0.000)
INTERACTION EFFECTS								
Mismatched job × Ever Unemployed…….	0.025	(0.127)	0.118	(0.265)	-0.011	(0.339)	0.281*	(0.060)
Overeducated[a] × Ever Unemployed………	-0.034	(0.126)	0.007	(0.487)	-0.062**	(0.022)	0.345**	(0.046)
Undereducated[a] × Ever Unemployed……..	-0.062***	(0.007)	-0.358	(0.187)	-0.007	(0.447)	-0.042	(0.466)
Differently educated[a] × Ever Unemployed..	-0.013	(0.317)	-0.058	(0.411)	-0.018	(0.305)	0.074	(0.379)
Employment contract[b] × Ever Unemployed	-0.038*	(0.067)	0.133	(0.249)	-0.176*	(0.066)	0.234*	(0.073)
Constant……………………………………	0.954***	(0.000)	0.743***	(0.000)	0.896***	(0.000)	0.008	(0.356)
Log Likelihood…………………………….	-1,431.2		32,983.4		-2,393.3		18,683.8	
Chi^2……………………………………...	15,157.4		931.3		7,563.7		888	

NOTE 1. ─ The dependent variable in sub-models (1) and (3) is the log of hourly wages, while in sub-models (2) and (4) the dependent variable is the squared residual. Each mean and variance sub-model also controls for the effects of additional covariates including education level, sector, marital status, occupational level, survey year as well as all time-varying covariates at their grand mean level (i.e., averaged over all periods).

NOTE 2. ─ a = Outdated education is the reference category; b = Permanent contract is the reference category;

NOTE 3. ─ *p* < .01; ** *p* < .05; * *p* < .1 (one-tailed tests).

APPENDIX A

TABLE 1A
DESCRIPTIVE CHARACTERISTICS BY EMPLOYMENT STATUS, 1986-2008

	EMPLOYED		EVER UNEMPLOYED	
	Mean	*SD*	*Mean*	*SD*
Log of hourly wage……………………..	2.43	0.39	2.29	0.41
Duration of unemployment (in months)...			18.69	19.01
Unemployment frequency……................			1.09	0.33
Age…………………………………...	39.88	11.64	37.58	11.76
Dutch…………………………………	0.93	0.26	0.88	0.32
Female………………………………..	0.42	0.49	0.59	0.49
Married……………………………….	0.77	0.42	0.65	0.48
Has home living children……………….	1.57	0.49	1.55	0.50
Lower Education Level…………………	0.37	0.48	0.44	0.50
Intermediate Level………………………	0.36	0.48	0.35	0.48
College/University………………………	0.26	0.44	0.20	0.40
Missing……………………………….	0.01	0.07	0.01	0.08
Overeducated……………………………	0.07	0.25	0.06	0.24
Undereducated…………………………..	0.02	0.13	0.01	0.11
Differently educated……………………	0.05	0.23	0.06	0.23
Outdated education……………………....	0.02	0.15	0.02	0.14
Mismatch………………………………..	0.14	0.34	0.12	0.32
Employment contract[b] (=temporary) …...	0.20	0.40	0.40	0.49
Tenure …………………………………..	32.44	20.32	28.67	20.99
ISEI level………………………………..	39.61	22.65	24.75	24.93
Agric, forestry, fisheries………………...	0.02	0.14	0.01	0.09
Retail & whole trade, repair serv………..	0.12	0.32	0.07	0.26
Construction……………………………..	0.05	0.22	0.03	0.17
Transportation…………………………...	0.13	0.34	0.10	0.30
Durable & non-durable manufactory……	0.06	0.23	0.03	0.17
Business Services……………………….	0.12	0.32	0.07	0.26
Professional Services……………………	0.14	0.35	0.09	0.29
Education Services……………………...	0.05	0.22	0.04	0.20
Governmental Services………………….	0.08	0.27	0.03	0.17
Other…………………………………….	0.08	0.27	0.04	0.19
Number of wage observations…………..	33,037		5,773	
Number of workers……………………...	13,174		2,110	

TABLE 1B

DESCRIPTION OF VARIABLES

VARIABLE NAMES	VARIABLE DEFINITION	VARIABLE CONSTRUCTION
Log of hourly wage…………………………	Natural log of current net hourly wage	Ln(Monthly net wage/monthly working hours).
Ever Unemployed……………………………	Time-dependent dummy variable for ever unemployment	Ever unemployment (1 = unemployed at the time of interview or in-between interview dates, 0 = continuously employed over the observation period).
Duration of unemployment (in months)...	Duration variable for the total length of unemployment duration of person *i*, over the observation period *t* with 0 those in continuous employment	Σ (End date of unemployment -/- Start date of unemployment).
Unemployment frequency……...............	Count variable for the number of unemployment spells of person *i* during the observation period *t* with 0 those in continuous employment	Σ (Count variable for the number of unemployment spells over the observation period).
Age…………………………………………..	Age in years	Age in years at time of interview.
Dutch……………………………………...	Country of birth	Dutch =1; and 0 if otherwise.
Gender………………………………………	Gender	Female=1; and 0 = Male.
Marital status………………………………...	Marital status at time of interview	1 = Married/Cohabiting and 0 if otherwise.
Has home living children……………………	Home living children at time of interview	1 = no; 2 = 1+ home living children.
Education level………………………………	Education level at time of interview	1= Completion of elementary education; 2= completion of lower and/or upper intermediate secondary school; 3= completion of a college or university degree.
Overeducated………………………………..	Overeducated in current job	Overeducated (1= yes; 0= otherwise).

Undereducated………………………………	Undereducated in current job	Undereducated (1= yes; 0= otherwise).
Differently educated…………………………	Differently educated in current job	Differently educated (1= yes; 0= otherwise).
Outdated education…………………………	Outdated education in current job	Outdated (1= yes; 0= otherwise).
Mismatch…………………………………….	Current job is mismatched	Mismatch (1=yes; 0=otherwise).
Employment contract………………………..	Type of current employment contract	Employment contract (0= permanent; 1= temporary employment contract).
Tenure……………………………………….	Tenure with the former employer	Σ (End date of employment -/- Start date of employment).
ISEI level…………………………………….	Current level of occupational status at the time of interview using the International Socio-Economic Index (ISEI) scale.	Continuous scale ranging from 10 to 90, with 0 for those with missing or no occupation level.
Industry………………………………………	Current industry	Dummies (11): governmental services; education services; professional services; business services; durable and non-durable manufacturing and mining; transportation; construction; retail trade and grocery, whole trade, repair services; agriculture; forestry; fisheries.
Sector………………………………………..	Current sector	0 = private; 1 = public sector.