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Estimating labour market transitions from labour force surveys

The case of Viet Nam

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Abstract

Labour market transitions that workers experience throughout their working life play an important role in current policy discussions surrounding the future of work. Transitions occur between employment, unemployment and inactivity, but also between formality and informality, as well as between different occupations or industries. This paper discusses methodologies that are available from the literature to estimate the incidence and frequency of transitions using data from labour force surveys, which are run as a rotating panel. The paper then applies these methodologies to Viet Nam in 2011-19, producing estimates of different types of labour market transitions. Without aiming to be comprehensive, this paper provides some examples of what type of data can be produced, demonstrating the feasibility and value of transitions data for labour market analysis.

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Introduction

Labour market transitions play an important role in current policy discussions surrounding the future of work. The Centenary Declaration for the Future of Work, adopted at the International Labour Conference (ILC) in June 2019, calls for "effective measures to support people through the transitions they will face throughout their working lives".[1] The Declaration also refers to the promotion of the transition from the informal to the formal economy, in line with the Transition from the Informal to the Formal Economy Recommendation (R204) adopted by the ILC in 2015. The Global Commission on the Future of Work, which was set in place by the International Labour Organization (ILO) as part of its Future of Work Initiative, mentioned in its 2019 report the "increasing number of labour market transitions" that workers will go through "over the course of their lives" (ILO, 2019). Even though labour market transitions have gained such a prominent role in current discussions, data on transitions is rather scarce, in particular in the context of developing countries, and often not produced on the basis of standard labour force surveys. In some instances, the design of labour force surveys inhibits the direct estimation of such data from the micro dataset. In other instances, however, the design would actually allow for the production of labour market transitions data, but the information needed to produce these data is simply not being used.

The purpose of this paper is to demonstrate how labour force surveys can be used to measure labour market transitions, highlighting the particular example of Viet Nam. Labour force survey data in Viet Nam are collected on a quarterly basis, using a rotating panel data approach, where each respondent in principle takes part in the labour force survey twice, over two consecutive quarters. In other words, households respond to the labour force survey questionnaire twice, which allows to track quarterly changes in an individual's job or labour market status. In such a setting, estimates on the prevalence of job-to-job transitions or any other types of labour market transitions can then be directly derived from the labour force survey, for Viet Nam as well as for any other country with a similar labour force survey design.

This paper relies on well-established methodologies that have been developed in the literature and applies these methodologies to Vietnamese labour force survey data for 2011-19 in order to produce data on labour market transitions for this time period. More specifically, the paper produces estimates of transitions into and out of employment, as well as within and across a broad set of job types – including transitions between formality and informality, between industries, and between occupations. The paper considers both 2- and 4-digit categories for industries and occupations.

Labour market transitions are useful to analyze labour markets. Cross-sectional surveys provide snapshots of the distribution of workers across various labour force statuses, formality statuses, industries, and occupations. However, changes in the stock of workers in any given category are driven by labour market transitions. Variations in job finding and job separation rates underlie fluctuations in the stock of employed and unemployed workers. Similarly, as the probability of finding a formal job rises, or the probability of separating from one declines, the number of formally employed workers increases. There are also transitions between industries and occupations, and workers that have a job in a particular industry or occupation might be more likely to move to another industry or occupation than other workers. Surveys with a panel structure allow measurements of these worker flows. Estimates of labour market transitions are thus informative of labour market dynamics and provide insight into current and future changes in the distribution of workers across the economy, which in turn can help policy making.

Worker flows across narrowly defined industries or occupations can provide important information about the evolution of the labour market that is unobserved when only considering transitions into and out of employment. Examples of insights that can be drawn from cross-industry or cross-occupation flows are

[1] The Centenary Declaration on the Future of Work is available here: https://www.ilo.org/global/about-the-ilo/mission-and-objectives/centenary-declaration/lang--en/index.htm.

abound. For instance, high transition rates can be indicative of the transferability of skills across occupations. The dynamics of cross-occupation or industry transitions across workers' lifecycles is informative for examining career progressions as well as for assessing whether labour market trajectories stabilize towards a particular occupation with workers' age. Transitions across occupations provide insights into each occupation's exposure to shocks.

Another use of labour market transitions data can be found in labour market forecasting. For example, instead of forecasting unemployment directly, it is possible to forecast separately the transitions into unemployment and the transitions out of unemployment. Forecasts of entries and exits into and out of the pool of unemployed workers then produce an implied forecast of overall unemployment. By separately estimating both components and understanding their individuals drivers, forecasting precision can increase (Barnichon and Nekarda, 2012; Barnichon and Garda, 2016). A similar argument can be made for predictions of the stock of workers in any given labour market category.

Moreover, variations in the employment rate within any job type, industry or occupation over time can be decomposed into changes in the inflow or outflow rate, or changes in the composition of the workforce. The inflow and outflow rates measure how many workers join or exit the pool of workers with a given job type, industry or occupation within a certain period of time. The composition of the workforce accounts for changes that are driven by a change in the prevalence of certain groups of workers in the total workforce, where these workers might be more or less likely to choose a particular job type, industry or occupation and therefore drive overall changes in the employment rate. This paper undertakes as an example a decomposition of the rise in formalization observed over time in Viet Nam. The change in the formality rate is decomposed into two channels: changes in the formality rate while holding the workforce composition in terms of gender, age, and educational attainment constant, and changes in the composition of the workforce while holding formality rates constant.

Section 1 of this paper provides a literature survey on the construction of measures of labour market transitions. Section 2 discusses the methodology used to construct data on labour market transitions for Viet Nam. Section 3 highlights some examples of the type of analyses that can be conducted with data on labour market transitions for Viet Nam. Section 4 introduces the results of a decomposition analysis for changes in formal employment in Viet Nam over time. The final section concludes.

1 Literature review

Measurement of labour market transitions

The large amount of research undertaken in recent decades on the dynamics of job loss and hiring underscores the importance of the measurement of labour market transitions, often in the literature referred to as flows. Early work on the topic focused on gross flows of workers between unemployment and employment. Hall (1972) and Feldstein (1973) highlighted the crucial role of turnover and transitions in understanding unemployment. In their work, the unemployed are not seen as a constant pool of individuals who want to work but are not doing so, even though they would be available for employment and are actively seeking work.[2] Instead, unemployment is seen as the result of changing rates of entry and exit of workers from and into jobs. Most individuals are unemployed for a short period of time, and only a few experience longer unemployment spells.

A vast literature seeks to understand the underlying determinants of the cyclical fluctuations in unemployment. Darby et al. (1986) find that increases in unemployment during recessions are attributable to a rise in the rate at which workers separate from their jobs. In contrast, Hall (2005) argues that adverse shocks increase unemployment through a decline in job finding rates rather than an increase in separations. Consistent with this latter argument, Shimer (2012) finds that most of the variation in the unemployment rate is due to changes in the job finding probability, as opposed to changes in the employment exit probability.

The literature then evolved to allow for multi-state transitions including, for example, inactivity or direct job-to-job transitions. Adding non-employment, Elsby et al. (2015) find that the labour force participation margin is important for understanding fluctuations in the unemployment rate. They conclude that analyses that focus on trends in stocks only, such as the share of the population that is inactive and hence out of the labour force, ignores the cyclicality of the underlying flows, such as the flows between unemployment and inactivity. Fallick and Fleischman (2001, 2004) focus on workers' movements across employers that occur without a non-employment spell. They similarly argue that overlooking these flows understates the dynamism in the labour market.

A related literature then analyzed the contribution of worker heterogeneity to job finding and separation probabilities. The "heterogeneity hypothesis" posed by Darby et al. (1985) is that during a downturn, the unemployed pool shifts towards a larger share of non-temporary layoffs. These workers have lower job finding probabilities. Thus, it is not that recessions are periods of particularly low outflows from unemployment, but rather that they are periods of high separation rates for a set of workers who are more likely to be unemployed for longer. The composition of the unemployment pool, and not changes in the overall job finding probability is what drives the changes in unemployment rates. Instead, Nakamura et al. (2020) argue that recessions lead to a composition effect that shifts the pool of unemployed workers towards higher skilled individuals, for whom it might be easier to move out of unemployment. This is because job separation rates increase even for this group of workers during downturns.

In the context of developing economies, the analysis of labour market transitions often focuses on transitions between formality and informality, and vice-versa. Given the vast prevalence of informal employment in many developing countries (ILO, 2018), which to a large extent determines workers' access to social protection, formal worker representation and other aspects of job quality and decent work, this margin of transition is particularly relevant for these countries. Bosch and Maloney (2007) consider five mutually

[2] See ILOSTAT for a precise definition of unemployment in accordance with the Resolutions of the International Conference of Labour Statisticians, available at: https://ilostat.ilo.org/resources/concepts-and-definitions/description-unemployment-rate/.

exclusive states across which workers transit in Mexico between 1987 and 2002: inactive, unemployed, informal self-employed, informal salaried and formal salaried. They find that while the cyclical properties in job finding and job separation probabilities are similar in Mexico and the US for formal salaried workers, the pattern is reverse for self-employment. Herrera et al. (2005) explore labour market transitions across different formality statuses in Peru. Tanzel and Ozdemir (2019) analyze the case of Egypt, while Gutierrez et al. (2019) focus on Bangladesh. These analyses underscore the usefulness of a flow approach, that considers transitions between formal and informal jobs, as opposed to a stock approach, which focuses on formality and informality rates at given points in time to study the evolution of the labour market.

Biases caused by attrition and misclassification error

Abowd and Zellner (1985) highlighted two issues that arise when estimating gross labour flows using rotating panel surveys. First, by construction, labour market transitions cannot be observed for individuals who are not matched on consecutive survey waves. Regardless of whether the inability to match observations across time arises as a result of temporary sample drop-outs, incomplete survey responses, or incorrect identifiers, these individuals' transitions are excluded from measures of labour market transitions. This gives rise to attrition or rotation group bias if the probability of its occurrence is not random. Second, measurement or classification error can arise when workers misreport their labour market situation, or when interviewers introduce errors when recording the survey response. Misclassification error usually cancels out or has a minimal effect on stocks but can substantially affect flow estimation. For example, if one worker who was unemployed in one survey wave is incorrectly classified as employed in the next survey wave, even though she has actually not changed her status, and if the reverse is true for another worker, the overall error that occurs when measuring stocks might cancel out. These two classification errors, however, do contribute to an over-estimation of transitions between employment and unemployment and vice-versa.

The existing literature developed various approaches to address attrition bias. The simplest approach is to rely on a "missing-at-random" (MAR) assumption. If there is no correlation between attrition probability and labour market transitions, then it is possible to simply drop the unmatched observations to estimate unbiased flows. However, analyses of various countries and time periods indicate that the missing at random assumption is unlikely to hold in most settings.[3]

There are different approaches to deal with non-random attrition bias. Donovan et al. (2020) use post-stratification of the sampling weights so that the distribution of the longitudinally matched sample resembles the distribution in the cross section. Fujita and Ramey (2009) propose an approach that minimizes the differences in the stocks derived from official cross-sectional data and stocks imputed from worker flows. Bleakley et al. (1999) and Fallick and Fleischman (2001), among others, use an approach similar to that employed by the Bureau of Labor Statistics (BLS) to reweight observation in the United States' Current Population Survey. The approach relies on estimating the attrition probability for different groups in the sample, and then using the inverse estimated match rate to reweight the observation in the sample.

Also classification error can be an important source of bias in labour market flows. Clark and Summers (1979) and Poterba and Summers (1986) discuss the potential concerns of spurious transitions arising from inconsistent reporting in survey data. They estimate the bias due to classification error and correct the bias using data from re-interviews.[4] Assaad et al. (2018) find important inconsistencies in cross-time reporting across different panel waves, even for time-invariant information, suggesting that classification error can be an important source of bias in some instances.

[3] See, for example, Ziliak and Kniesner (1998), Bleakley et al (1999) and Fujita and Ramey (2009) for the United States; Assaad et al. (2018) for Egypt; Donovan et al. (2020) for a large set of countries.

[4] A re-interview refers to the second interview of a selected number of households or respondents, typically conducted shortly after the first one, using the same survey questions and same reference period.

Biases caused by time aggregation

Shimer (2012) highlights the importance of time-aggregation bias when analyzing labour market flows measured in discrete time intervals. Time aggregation bias occurs because data on a worker's situation in the labour market are not observed continuously, but only at discrete time intervals such as quarters in the case of a quarterly survey. Transitions that occur within this time interval are not observed. In the context of transitions into and out of employment, "Ignoring time aggregation will bias a researcher towards finding a countercyclical employment exit probability, because when the job finding probability falls, a worker who loses her job is more likely to experience a measured spell of unemployment" (Shimer, 2012, p. 129). Shimer (2012) corrects for this bias by explicitly working in a continuous time model in which data are available at discrete intervals.

2 Methodology

Data

This paper next estimates gross worker transitions and transition probabilities for Viet Nam in 2011-19.[5] The paper uses micro-level data on individuals' employment status and job type in consecutive quarters, available from Viet Nam's quarterly labour force survey, to construct time series for the gross transitions of workers into and out of a given labour market status.

Viet Nam's labour force survey is run as a rotating panel, in which each quarter includes data from newly surveyed households for about half of the observations, while the remaining half of the observations correspond to households that were first surveyed in the previous quarter. However, individuals can only be tracked between different quarters within a year, not across years. Transitions can hence be calculated between Q1 and Q2, between Q2 and Q3, and between Q3 and Q4 for every year; they cannot be calculated between Q4 of one year and Q1 of the next year. In line with ILO definitions, individuals who during the first of the two survey waves are under 15 years old are excluded. Furthermore, individuals which for any reason cannot be unambigously tracked over two different quarters are excluded[6], as well as those who are followed in non-consecutive waves, or who appear to be followed for more than two waves in the survey.

The number of individuals that can be tracked across different quarters varies slightly over time. On average across all quarterly pairs of surveys, the number of individuals that can be tracked is about 65,000. The number varies between 56,000 and 85,000 in 2011-19.[7]

Gross transitions

The paper examines gross labour market transitions across four different labour market categories. These categories, and the corresponding, mutually exclusive labour market statuses that encompass them, are:

1. **Labour force status** (LFS): employed, unemployed, out of the labour force.
2. **Formal job** (FNJ): employed with a formal job, employed with an informal job, not employed.[8]
3. **Industry** (IND): 86 2-digit or 524 4-digit industry classification categories, plus a not employed group.
4. **Occupation** (OCCU): 11 2-digit or 568 4-digit industry classification categories, plus a not employed group.

Let $C \in \{LFS, FNJ, IND, OCCU\}$ be the set of these 4 categories, labelled as *c*. Each *c* is composed of s_c mutually exclusive statuses. For each possible pair of statuses (*j*,*k*) in category *c,* the paper calculates flows from state *j* in quarter *t* to state *k* in quarter *t+1* as the weighted sum of all individuals who transition between these two states

[5] Prior to 2013, the necessary information to identify formal and informal jobs was not available. Therefore, for these time series the sample is limited to the period between 2013 and 2019.
[6] Section 1 of this paper discusses approaches to re-weigh transition estimates to account for attrition.
[7] It varies between 59,000 and 69,000 in 2013-19, which is the time period for which data on the formality status of the job are available.
[8] Transitions for which results are shown in this paper rely on the concept of informality by nature of job (formal job, informal job). Even though results are not shown in this paper, transitions were also estimated on the basis of the concept of informality by type of production unit (formal sector, informal sector, household). For detailed information on the different concepts of informality, see https://ilostat.ilo.org/resources/concepts-and-definitions/description-informality/. ILO (2013) provides details on the measurement of the informal sector and informal employment.

$$N(j,k)_t = \sum_i I[c_{i,t} = j, c_{i,t+1} = k] \times \omega_i \quad (1)$$

The quarterly transition probabilities out of state *j* into state *k* in period *t* are obtained by dividing the weighted flows by the weighted sum of all individuals in state *j* in period *t*.

Weights

In all cases, the analysis in this paper considers two possible weight: sampling weights and attrition revised weights. The former uses the sampling weights provided by Viet Nam's General Statistics Office as frequency weights, without any further adjustment. These weights are meant to reflect the occurrence of each observation in the general population of Viet Nam. Tables and figures presented in this paper show the sampling weights estimates.

For the attrition revised weights, the paper follows Fallick and Fleischman (2001) and uses attrition weighted inverse probability weights. The approach relies on estimating the attrition probability for different groups in the sample, and then using the inverse estimated match rate to reweight the observation in the sample. To do so, in a first step, probit models of attrition are estimated for each quarter in the data using equation (2) where $attrit_{i,t}$ is an indicator variable equal to 1 if individual *i* who is in the survey's sample on quarter *t* cannot be matched to an observation in period *t+1,* and zero otherwise. γ_g^t are a set of fixed effects for the 3-way interaction between *i*'s gender, labour force status[9], and age group in 10-year age bins. These effects are allowed to vary by quarter.

$$attrit_{i,t} = \sum_g \gamma_g^t + \epsilon_{i,t} \quad (2)$$

Then, the predicted attrition probability for each group *g* is used to estimate a relative attrition probability and scale the sampling weights using the relative attrition probability.

$$\omega_i^{att} = \omega_i \times \frac{\widehat{attrit_{i,t}}}{attrit_t} \quad (3)$$

where ω_i is individual *i*'s sampling weight and $attrit_t$ is equal to 1 minus the share of matched observations in quarter *t*. By rescaling the sampling weights in this manner, our estimation gives more weight to transitions by individuals in groups who are more likely to drop off the sample thus compensating for their higher attrition rate.

Given that the Viet Nam labour force survey only tracks households for two consecutive quarters, plus the lack of data on re-interviews, this paper does not attempt to assess the extent of classification errors or make any corrections to account for their existence. In this regard, it is just worth to point out that estimates of labour market transitions that involve more disaggregated labour market categories (such as 4-digit industry or occupation classifications) are likely to suffer more from this type of bias. However, there is no unusual increase in gross flows between categories across different levels of disaggregation, which to some extent assuages concerns of misclassification.

9 Employed, unemployed, or out of the labour force.

Time aggregation

This paper follows Gomes (2015) and uses the quarterly labour force survey data to extrapolate monthly transition rates across labour market states. Continuous transitions are calculated by taking the limit of the extrapolated transition matrix, as time elapsed between observations tends to zero.

Following Gomes (2015), let n_q be the $s_c \times s_c$ square, quarterly transition matrix obtained from quarterly data for labour market status category C. Then, the monthly transition matrix, $\widehat{n}_m$, is estimated as follows:

$$\widehat{n}_m = p_q \mu_q^{1/3} p_q^{-1} \tag{4}$$

where μ_q is the diagonal matrix of eigenvalues for matrix n_q and p_q is a matrix of its eigenvectors. We then obtain the continuous time transition rates from the off-diagonal elements of the matrix $\hat{\lambda} = \lim_{\Delta \to 0} \frac{p_q \mu_q^{\Delta} p_q^{-1} - I}{\Delta}$ where I is the identify matrix.

Ideally, in order to assess the accuracy of this approach, one would like to compare these extrapolated monthly transition rates to those estimated from data collected on a monthly basis. As Viet Nam's labour force survey data have quarterly frequency, there is no possibility to make such a comparison with data from a monthly-level database.

3 Results

Without aiming to be comprehensive, this section presents a selected set of labour market transitions data for Viet Nam, which aim to serve as examples of the types of analyses that can be done with these data. As results that correct for the attrition bias and results that do not are in general very similar, results in this section are only shown for transitions that were estimated on the basis of unadjusted sampling weights.

Labour force status

The first and second rows of Figure 1 show, respectively, inflow and outflow probabilities from employment in Viet Nam from 2011 to 2019. Each panel shows quarterly transition probabilities into and out of employment, from and into unemployment and inactivity, respectively. Figure 1 also shows the extrapolated monthly probability calculated using equation (4) above, as well as the continuous transition rate.

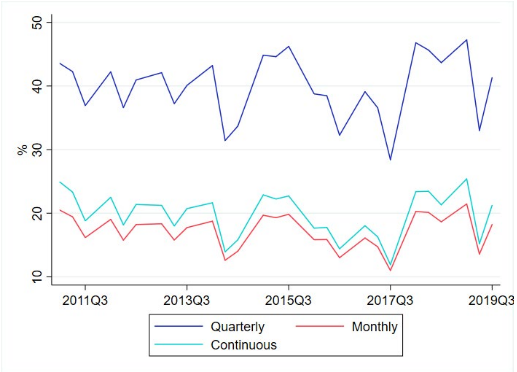
Individuals flow into employment from either unemployment or inactivity. Not surprisingly, comparing panels (a) and (b) in the first row of Figure 1, indicates that the job finding probability is approximately four times larger for unemployed individuals than for those who are inactive. But for a short-lived decline in 2016, the quarterly job finding probability from unemployment was relatively stable throughout the period at a mean value of 40 per cent and a standard deviation of 5 percentage points without taking into account seasonal variation. In other words, workers that are unemployed in one quarter have a probability of 40 per cent of being in employment in the next quarter.

Job separations to inactivity are more likely than separations to unemployment, although it is important to note that outflows to unemployment may be underestimated if unemployment spells are shorter than three months and hence unobserved at a quarterly frequency. In other words, there could be some individuals that upon losing their job become unemployed, but find a new job in less than three months time, which makes them appear in the labour force survey as continuously being in employment. After 2015, quarterly job separations into unemployment declined from a peak of 0.6 per cent to under 0.2 per cent by the end of 2018.

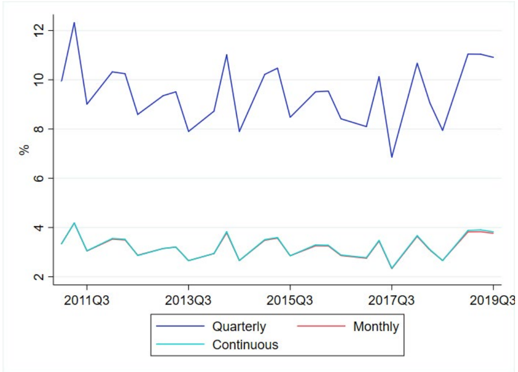
Figure 2 depicts transitions probabilities between unemployment and inactivity. The quarterly transition probability from unemployment to inactivity declined from 27 to around 10 per cent between 2011 and 2015, before rising again more recently to above 20 per cent. The probability for an inactive worker to become unemployed has been on a declining trend.

▶ Figure 1. Job finding and job separation probabilities

a) Unemployment to employment

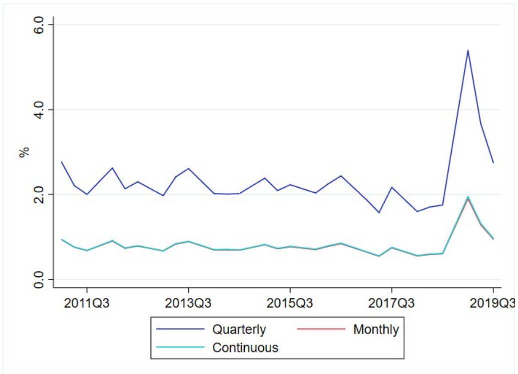


b) Inactivity to employment



c) Employment to unemployment

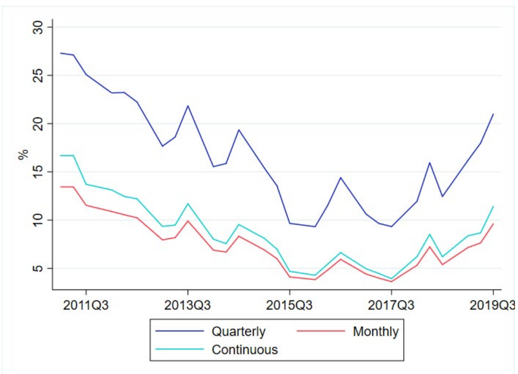
d) Employment to inactivity



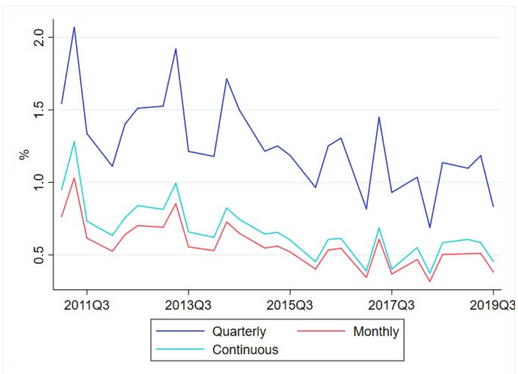
Notes: The data series that are shown use (unadjusted) sampling weights. See section 2 for more details. Breaks observed for some data series between 2018 and 2019 might be driven by a major revision of sampling weights.

▶ Figure 2. Transition probabilities between unemployment and inactivity

a) Unemployment to inactivity



b) Inactivity to unemployment



Notes: See figure 1 notes.

Table 1 shows the average quarterly transition probabilities, the mean continuous transition rates and their standard deviations. Note that because they are calculated by taking the limit as time intervals shrink to zero from extrapolated monthly rates (see equation (4)), the estimated continuous transition rates are closer to the transitions that occur per month, rather than per quarter. Multiplying the continuous rate by 3 makes both rates more directly comparable.

▶ **Table 1. Transition probabilities (per cent) and volatility in labour market status, 2011-19 (average)**

		From employment		From unemployment		From inactivity	
	To:	Unemployment	Inactivity	Employment	Inactivity	Employment	Unemployment
Mean	Quarterly	0.4	2.3	39.9	16.9	9.5	1.3
	Continuous	0.2	0.8	19.8	8.9	3.3	0.7
Std. Dev.	Quarterly	0.1	0.7	5.1	5.5	1.3	0.3
	Continuous	0.1	0.3	3.6	3.6	0.5	0.2

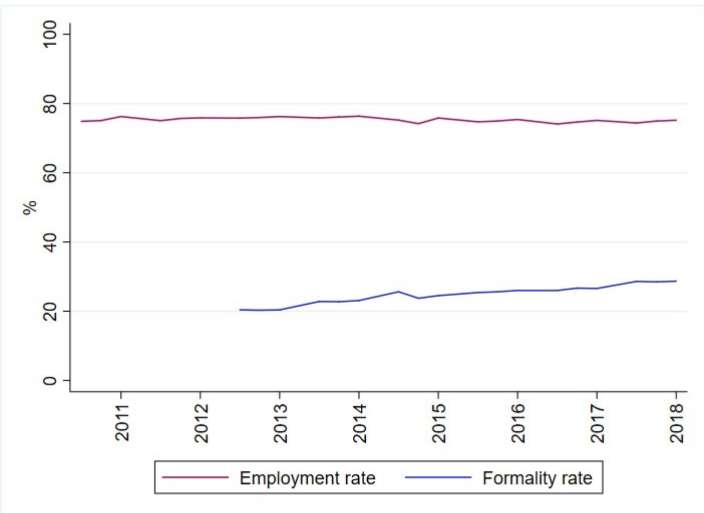
Notes: The data points that are shown were calculated on the basis of (unadjusted) sampling weights. See section 2 for more details. They correspond to the simple average of quarterly transition probabilities and continuous transition rates in 2011-19.

Formality

This section focuses on formality as defined by the nature of the job, which is for example determined by whether the worker has access to social security schemes. Figure 3 shows a relative stable overall employment rate between 2011 and 2018. However, the share of employed workers in formal jobs increased steadily from 20 to close to 30 per cent between 2013 and 2018.

The increase in formalization was not equally experienced by all groups in the workforce. Figure 4 separately calculates the share of formal employment by education levels for men (panel (a)) and women (panel (b)). Women with basic and intermediate education observed the largest increase in formalization (of 9 and 8 percentage points, respectively). The same education groups also had the largest increase for men (6 and 7 percentage points).

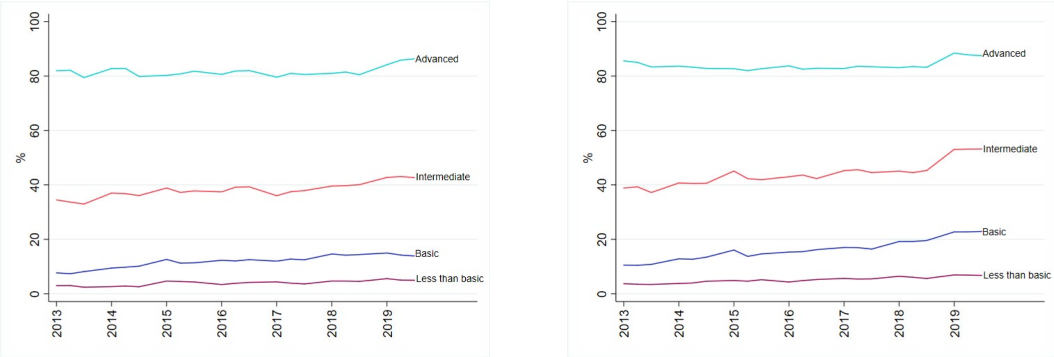
▶ **Figure 3. Employment and formality rates**



Notes: The employment rate was calculated as the share of employment in the working-age population. The formality rate was calculated as the share of formal employment in total employment.

▶ Figure 4. Formality rates by sex and level of educational attainment

a) Formality rates among men   b) Formality rates among women



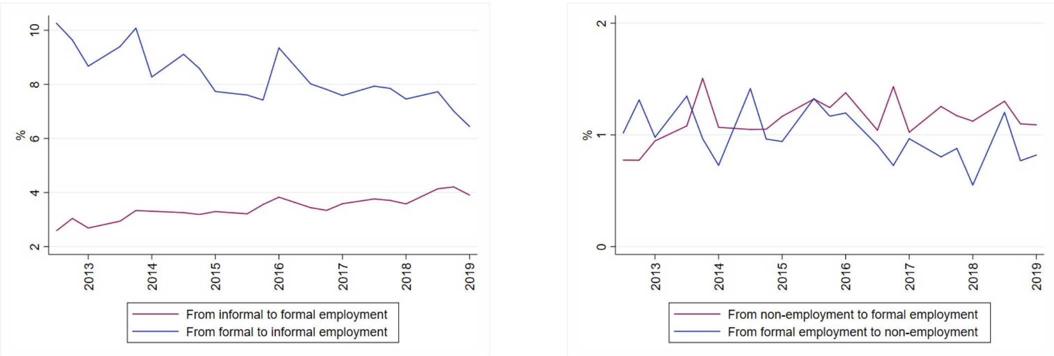
Notes: The formality rates shown in this figure were calculated as the share of formal employment in total employment by sex and level of educational attainment.

Figure 5 shows the quarterly transition probabilities (using sampling weights) from and to formal employment. Panel (a) presents transitions between formal and informal jobs without an observed non-employment spell, while panel (b) shows transitions between formal jobs and non-employment. These time series indicate that the increase in the share of workers in formal employment shown in Figure 3 can be attributed to a decrease in the separation rate of formal workers to informal jobs (from 9 to 7 per cent between 2013 and 2018) and an increase in inflows to formal jobs from informal employment (from 3 to 4 per cent within the same period). Formal jobs became more stable, and more likely to find for informally employed individuals.

Panel (b) shows that the same is not true for unemployed and inactive workers. The probability of transitioning to a formal job from non-employment remained stable around 1 per cent, as did separations from formal jobs to non-employment. It is important to note that these findings may be affected by time aggregation bias. It may be the case that transitions between informal and formal jobs shown in panel (a) are mediated by unobserved periods of non-employment. However, the quarterly frequency in the survey data plus the lack of granular information on unemployment spell durations does not allow us to correct for this further. Regardless of whether the transitions are mediated through unemployment spells or not, it is interesting to see that individuals with an informal employment spell a quarter prior are more likely to transition to a formal job than those without it.

▶ Figure 5. Formal job finding and job separation probabilities

a) From/to informal employment   b) From/to non-employment



Notes: The data series that are shown were calculated on the basis of (unadjusted) sampling weights. They show quarterly transition probabilities.

Industry

Workers' industry or sector of employment is grouped into categories using the 2 and 4-digit level of the International Standard Industrial Classification of All Economic Activities (ISIC). At the 2-digit level, there are 86 industries of which 10 categories consistently encompass three-quarters of the employed population in Viet Nam between 2011 and 2019.

This section provides an overview of labour market transitions between economic sectors at the 2-digit level. The section considers outflows to a different economic sector that occur without an observed non-employment spell (cross-sector job-to-job transitions), and outflows to non-employment. Table 2 presents the average quarterly outflow probabilities from each sector *s* to a different sector *-s*, $outflow_{s,-s}$, and the outflow probability from sector s to non-employment, $outflow_{s,\,nonemp}$, which are respectively calculated as follows:

$$outflow_{s,-s} = \frac{1}{T}\sum_t \left[1 - \left(\frac{\sum_{i\in\{t\&t+1\}} \omega_i \times I[ISIC2_{i,t} = s\ \&ISIC2_{i,t+1} = -s]}{\sum_{i\in\{t\&t+1\}} \omega_i \times I[ISIC2_{i,t} = s]} + outflow\ rate^t_{s,\,nonemp}\right)\right]$$

$$outflow_{s,\,nonemp} = \frac{1}{T}\sum_t outflow\ rate^t_{s,\,nonemp} = \frac{1}{T}\sum_t \frac{\sum_{i\in\{t\&t+1\}} \omega_i \times I[ISIC2_{i,t} = s\ \&\ LFS_{i,t+1} \neq emp]}{\sum_{i\in\{t\&t+1\}} \omega_i \times I[ISIC2_{i,t} = s]}$$

where $i \in \{t\ \&\ t+1\}$ refers to the set of individuals that we can match in the labour force survey in the consecutive quarters *t* and *t+1*, and ω_i corresponds to the sampling weight for individual *i*. $ISIC2_{i,t}$ denotes the ISIC 2-digit level sector in which individual *i* is employed in quarter t. $LFS_{i,t+1}$ denotes the labour force status of individual *i* in quarter $t+1$, where emp stands for employed.

On average, 13.3 per cent of workers transition to a different sector in consecutive quarters without an observed unemployment or inactivity spell. "Financial service activities, except insurance and pension funding", "Education", and "Human health activities" are the sectors with the lowest probabilities of transition to another economic sector. At the other end of the spectrum, 68 per cent of all workers in "Information service activities" on average transition to a different sector in the following quarter. Various factors are likely to account for differences in the probablities to transit to another sector, including skills requirements, sectoral differences in wages, informality rates or other job quality indicators. For the vast majority of 2-digit economic sector categories (82 out of 86) the most likely average outcome for a worker is to remain in his or her current economic sector.

Table 2. Quarterly job-to-job transitions to a different sector and quarterly transitions to non-employment (per cent), 2011-19 (average)

ISIC 2-digit code and description	Outflow probabilities (%)	
	To new sector	To non-employment
Total Transitions	**13.3**	**2.7**
63 - Information service activities	68.8	3.9
70 - Activities of head offices; management consultancy activities	61.7	0.0
02 - Forestry and logging	50.8	3.2
33 - Repair and installation of machinery and equipment	49.9	1.9
94 - Activities of membership organizations	47.7	5.5
66 - Activities auxiliary to financial service and insurance activities	45.6	0.0
81 - Services to buildings and landscape activities	44.2	2.1
59 - Motion picture, video and television programme production, sound recording and music publishing activities	43.3	0.6
19 - Manufacture of coke and refined petroleum products	42.5	2.1
90 - Creative, arts and entertainment activities	41.7	1.7
42 - Civil engineering	41.3	1.7
75 - Veterinary activities	40.5	1.0
37 - Sewerage	40.4	0.9
28 - Manufacture of machinery and equipment n.e.c.	40.2	1.6
82 - Office administrative, office support and other business support activities	40.2	2.6
77 - Rental and leasing activities	37.0	3.0
43 - Specialized construction activities	35.0	1.8
87 - Residential care activities	34.4	3.5
52 - Warehousing and support activities for transportation	34.0	1.8
32 - Other manufacturing	33.9	2.9
74 - Other professional, scientific and technical activities	32.7	1.6
29 - Manufacture of motor vehicles, trailers and semi-trailers	32.6	1.0
46 - Wholesale trade, except of motor vehicles and motorcycles	32.5	1.9
71 - Architectural and engineering activities; technical testing and analysis	31.9	1.1
08 - Other mining and quarrying	31.8	3.2
62 - Computer programming, consultancy and related activities	31.3	1.1
07 - Mining of metal ores	31.1	1.4
38 - Waste collection, treatment and disposal activities; materials recovery	30.7	1.9
78 - Employment activities	30.1	1.6
16 - Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	30.1	2.7
91 - Libraries, archives, museums and other cultural activities	29.2	0.1
95 - Repair of computers and personal and household goods	28.9	1.7
20 - Manufacture of chemicals and chemical products	28.9	1.6
93 - Sports activities and amusement and recreation activities	28.8	3.1
72 - Scientific research and development	28.8	0.6
99 - Activities of extraterritorial organizations and bodies	28.3	0.4
27 - Manufacture of electrical equipment	28.3	1.2
53 - Postal and courier activities	27.5	0.7

ISIC 2-digit code and description	Outflow probabilities (%)	
	To new sector	To non-employment
06 - Extraction of crude petroleum and natural gas	27.2	4.5
13 - Manufacture of textiles	27.1	2.0
24 - Manufacture of basic metals	26.6	1.4
22 - Manufacture of rubber and plastics products	26.5	1.8
58 - Publishing activities	25.4	1.9
69 - Legal and accounting activities	24.6	1.4
11 - Manufacture of beverages	24.2	2.1
97 - Activities of households as employers of domestic personnel	24.1	6.1
80 - Security and investigation activities	23.9	2.9
17 - Manufacture of paper and paper products	22.9	2.9
36 - Water collection, treatment and supply	22.6	1.0
79 - Travel agency, tour operator, reservation service and related activities	22.2	2.2
18 - Printing and reproduction of recorded media	22.0	2.0
21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations	22.0	0.5
60 - Programming and broadcasting activities	22.0	0.8
50 - Water transport	21.2	1.5
30 - Manufacture of other transport equipment	20.0	1.9
96 - Other personal service activities	19.9	2.5
73 - Advertising and market research	19.8	1.3
51 - Air transport	19.4	0.7
61 - Telecommunications	19.3	2.0
25 - Manufacture of fabricated metal products, except machinery and equipment	17.3	1.7
26 - Manufacture of computer, electronic and optical products	17.0	1.7
10 - Manufacture of food products	16.8	3.0
12 - Manufacture of tobacco products	15.3	2.5
47 - Retail trade, except of motor vehicles and motorcycles	14.9	2.3
31 - Manufacture of furniture	14.9	1.2
03 - Fishing and aquaculture	14.8	3.4
68 - Real estate activities	14.8	4.4
35 - Electricity, gas, steam and air conditioning supply	14.7	1.1
41 - Construction of buildings	14.6	1.6
55 - Accommodation	14.0	3.0
23 - Manufacture of other non-metallic mineral products	13.5	1.3
65 - Insurance, reinsurance and pension funding, except compulsory social security	11.7	1.9
45 - Wholesale and retail trade and repair of motor vehicles and motorcycles	11.7	1.7
49 - Land transport and transport via pipelines	11.7	1.5
56 - Food and beverage service activities	10.5	3.0
15 - Manufacture of leather and related products	8.7	1.5
14 - Manufacture of wearing apparel	8.7	2.2
92 - Gambling and betting activities	8.5	3.4
84 - Public administration and defense; compulsory social security	8.5	1.0
01 - Crop and animal production, hunting and related service activities	8.3	4.1

ISIC 2-digit code and description	Outflow probabilities (%)	
	To new sector	To non-employ-ment
64 - Financial service activities, except insurance and pension funding	6.1	1.1
86 - Human health activities	5.7	0.9
85 - Education	3.4	1.1

Notes: The data points that are shown use (unadjusted) sampling weights. See section 2 for more details. They correspond to the simple average of quarterly transition probabilities in 2011-19.

To provide an example of the type of analysis that can be done with transitions, this section looks at whether transitions out of an economic sector covary with wage growth in the sector. This analysis can provide some preliminary evidence on whether transitions across sectors accompany wage growth, with workers leaving sectors in decline for sectors experiencing wage growth. To do so, the median and average monthly wage for salaried employees is calculated in each 2-digit sector per quarter. To prevent outliers from having too much weight on the average wage, wages are winsorized at 1 per cent.

Figure 6 panel (a) indicates that there is a negative correlation between the 2011-18 growth of the average wage of a sector and the average cross-sector outflow probability. Consistent with workers seeking opportunities in sectors with better wage growth prospects, the sectors that experienced smaller wage growth in the period are those that on average have higher outflow probabilities to other sectors. The average probability of transitions to non-employment does not appear to be correlated with wage growth (panel (b)).

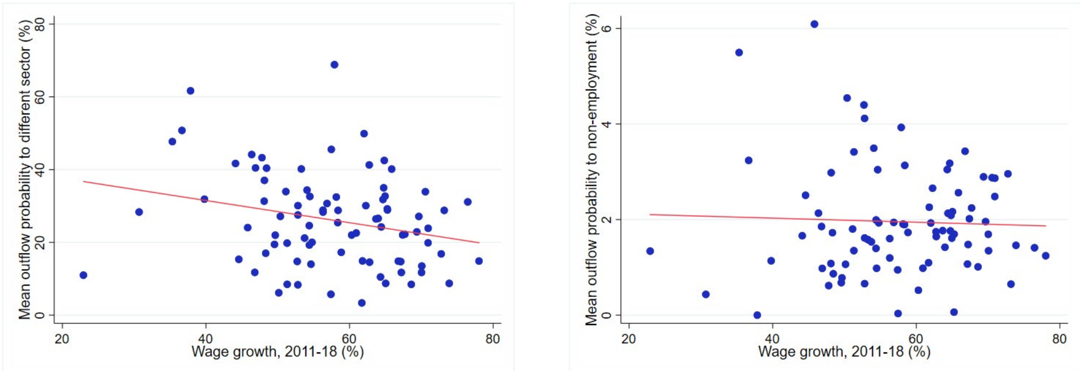
▶ **Figure 6. Sectoral outflow probabilities and sectoral wage growth**

Panel (a)

Job-to-job transitions to another sector

Panel (b)

Transitions to non-employment



Notes: Mean outflow probability corresponds to the average quarterly outflow probability in 2011-18, calculated on the basis of (unadjusted) sampling weights. See section 2 for more details. Wage growth in 2011-18 was calculated as the change in the natural logarithm of the average sectoral wage between 2011 Q3 and 2018 Q3. Each dot corresponds to one sector at the ISIC 2-digit level.

Occupation

Workers' occupation is grouped into categories using the 2 and 4-digit level of the International Standard Classification of Occupations (ISCO-08). At the 2-digit level, there are 10 occupational categories plus a "Not Elsewhere Classified" group. In the following, this section provides an overview of labour market transitions out of different occupations at the 2-digit level.

Table 3. Quarterly job-to-job transitions to a different occupation and quarterly transitions to non-employment (per cent), 2011-19 (average)

ISCO 2-digit code and description	Outflow probabilities	
	To new occupation	To non-employment
Total Transitions	**15.3**	**2.7**
4 - Clerical support workers	37.0	2.0
3 - Technicians and associate professionals	30.4	1.4
6 - Skilled agricultural, forestry and fishery workers	23.1	3.5
0 - Armed forces occupations	21.8	0.8
7 - Craft and related trades workers	17.8	1.9
1 - Managers	17.3	0.8
8 - Plant and machine operators, and assemblers	15.2	1.4
9 - Elementary occupations	12.7	3.9
2 - Professionals	11.8	0.8
5 - Service and sales workers	10.4	2.5

Notes: The data points that are shown use (unadjusted) sampling weights. See section 2 for more details. They correspond to the simple average of quarterly transition probabilities in 2011-19.

As shown in Table 3, on average 15.3 per cent of workers transition to a job in a different occupation without an observed unemployment spell. Cross-occupation transition probabilities range from 37 per cent for clerical support workers, to 10.4 per cent for service and sales workers. Table 4 presents the average quarterly transition matrix across all occupation categories. The shaded diagonal shows the average percentage of workers who remain in the same occupation in the following quarter. The most common outcome for an employee is to remain in the same occupation. Conditional on switching occupations (without a non-employment spell), there is some indication that workers seek occupations that are to some extent similar to their previous one. For example, the most like cross-occupation outflow for managers is to the professionals category. The most likely transition from agricultural, forestry, and fishing occupations, conditional on switching, is towards elementary occupations, and vice versa.

Table 4. Quarterly occupational transition matrix, 2011-2019 (average)

Current quarter's occupation (code – description)	Next quarter's occupation (code) 1	2	3	4	5	6	7	8	9	0	X	NE
1 - Managers	82	7	2	3	2	0	1	0	1	0	0	1
2 - Professionals	1	87	5	2	2	0	1	0	0	0	0	1
3 - Technicians and associate professionals	1	11	68	5	6	0	4	2	2	0	0	1
4 - Clerical support workers	2	8	10	61	8	1	2	2	4	0	0	2
5 - Service and sales workers	0	1	1	1	87	1	1	1	5	0	0	2
6 - Skilled agricultural, forestry and fishery	0	0	0	0	2	73	2	0	19	0	0	4
7 - Craft and related trades workers	0	0	1	0	2	1	80	5	8	0	0	2
8 - Plant and machine operators assemblers	0	0	1	1	1	1	7	83	5	0	0	1
9 - Elementary occupations	0	0	0	0	2	5	3	1	83	0	0	4
0 - Armed forces occupations	1	8	3	3	5	0	1	1	1	77	0	1
X - Not elsewhere classified	4	12	15	8	1	6	15	6	14	0	0	17
Not Employed	0	0	0	0	2	1	1	1	5	0	0	89

Notes: The data points that are shown use (unadjusted) sampling weights. See section 2 for more details. They correspond to the simple average of quarterly transition probabilities in 2011-19. Each cell shows the transitions from one occupation in one quarter to the same or another occupation in the next quarter. All rows and columns add up to 100 per cent; any difference is due to rounding.

4 Decompositions

The labour flow approach is based on the intuition that labour markets are not static but dynamic. Changes in the share of individuals in any given labour market state (such as unemployed, employed in a certain sector, employed in a certain occupation or formally employed) are the result of fluctuations in the number of individuals who transition into that state, and variations in those who leave that state. The probabilities to transit into and out of that labour market state may vary between different socio-economic groups. This implies that socio-demographic transitions may have an impact on the share of individuals in a given state on the labour market.

This section implements a decomposition for the change in the rate of formal employment between 2013 and 2018 as an example.[10] The decomposition could be instead performed on the change of any other employment category share. However, a decomposition of changes in the rate of formal employment might be a particular interesting example, as the formality rate has seen a continous upward trend, with an increase from 20.4 to 28.7 per cent, that is, an 8.3 percentage point increase, from the third quarter of 2013 to the third quarter of 2018.

Let g = 1, 2, ..., G be a mutually exclusive set of G groups of workers in a population. Let $\omega_{g,0}$ and $\omega_{g,1}$ be the share of workers in group g at time 0 and time 1, respectively. Finally, let $f_{g,0}$ and $f_{g,1}$ be the formality rate within each group g, which corresponds to the share of workers in group g that have a formal job, at time 0 and 1, respectively.

Then, the total formality rate in period t, f_t, can be obtained by using the weighted average of each group's formality rate:

$$f_t = \sum_g \omega_{g,t} \times f_{g,t} \tag{5}$$

The change in the formality rate between time 0 and 1 can be written as:

$$\Delta f = \sum_g \left(\omega_{g,1} \times f_{g,1} - \omega_{g,0} \times f_{g,0}\right) \tag{6}$$

One can re-write this equation as a function of changes in ω_g and f_g:

$$\Delta f = \sum_g \left(\underbrace{\omega_{g,0}\left(f_{g,1} - f_{g,0}\right)}_{A} + \underbrace{f_{g,1}(\omega_{g,1} - \omega_{g,0})}_{B} \right) \tag{7}$$

The first component of equation (7), part A, is what is typically referred to as the "coefficient effect" in the decomposition analysis. It isolates the change in the overall formality rate due to changes in the formality rate of each group assuming that there is no change in the participation rate for each group.

[10] In 2019, there was a major revision in survey weights, which is why the period was chosen to end in 2018.

The second component of equation (7), part B, is the "composition effect" in the decomposition analysis. This component isolates the change in formality rate that would have occurred due to changes in participation rates across groups only, with no changes in within-group formality rates.

The approach follows closely Maurizio and Vásquez (2019) who decompose the change in formality rates in five countries (Argentina, Brazil, Ecuador, Paraguay, and Peru), except for two important differences. First, the "composition effect" is measured through $f_{g,1}(\omega_{g,1} - \omega_{g,0})$ in equation (7), as opposed to $f_{g,0}(\omega_{g,1} - \omega_{g,0})$ which is used in Maurizio and Vásquez (2019). While there is conceptually no difference between the two approaches, given the assumption that within-group formality rates are assumed unchanged ($f_{g,0} = f_{g,1}$) when isolating the "composition effect", the advantage of this section's approach is that it ensures that the "coefficient effect" and the "composition effect" add up exactly to the overall change in the formality rate. Second, the decomposition presented in this section allows for flexible interaction across gender, age and educational attainment categories insted of using a unidimensional decomposition.

Using equation (7), the increase in the formality rate by 8.3 percentage points between the third quarter of 2013 and the third quarter of 2018, is decomposed into the "coefficient effect" and the "composition effect" – overall and for different gender-age-education-specific groups. The first row in Table 5 shows the main result of the decomposition analysis: approximately three-fourths of the increase (6.3 out of the 8.3 percentage point increase) can be attributed to the "coefficient effect," that is, to the increase in formalization rates within gender-age-education-specific groups. The remainder is due to a change in the composition of the workforce. This result is not too surprising given the short time-interval considered in the analysis: compositional shifts are expected to take longer to occur in the absence of major shocks or policy reforms. However, it is important to note that most of the "composition effect" is driven by increases in the share of educated women in the workforce.[11] This group of workers has a relatively high formality rate, and at the same time increased in size between 2013 and 2018. Consistent with Figure 3, changes in the formalization rate for men and women with basic and intermediate education drive most of the "coefficient effect."

[11] This can be seen by adding the estimated coefficients for the composition effect for females with "Intermediate" and "Advanced" education across all age groups.

Table 5. Decomposition analysis: Share of employment in formal jobs, 2013 Q3 - 2018 Q3

	Formality rate (per cent)		Participation rate (per cent)		Change in formality rate (percentage points)	Change in participation rate (percentage points)	Coefficient effect	Composition effect
	2013Q3	2018Q3	2013Q3	2018Q3				
All	20.4	28.7	100.0	100.0	8.3	0.0	6.33	1.96
Education x Gender x Age								
Male 15-24								
Less than basic	2.1	6.1	0.5	0.3	3.9	-0.2	0.02	-0.01
Basic	5.8	13.1	4.9	3.9	7.3	-1.0	0.36	-1.30
Intermediate	20.9	31.7	2.1	1.7	10.8	-0.4	0.23	-1.30
Advanced	51.9	60.9	0.4	0.4	9.0	0.0	0.04	0.00
Male 25-34								
Less than basic	3.5	5.5	1.3	0.8	1.9	-0.4	0.02	-0.02
Basic	10.1	18.8	5.5	5.5	8.6	-0.1	0.48	-0.01
Intermediate	37.2	44.7	3.6	3.6	7.5	0.0	0.27	-0.01
Advanced	80.1	79.7	1.8	2.4	-0.4	0.6	-0.01	0.48
Male 35-44								
Less than basic	3.1	5.7	1.8	1.7	2.7	-0.1	0.05	-0.01
Basic	10.6	17.6	6.9	6.8	7.1	-0.1	0.48	-0.02
Intermediate	39.6	49.9	2.5	2.3	10.3	-0.2	0.26	-1.20
Advanced	90.7	88.4	1.2	1.9	-2.3	0.7	-0.03	0.63
Male 45-54								
Less than basic	2.3	4.8	1.5	1.7	2.5	0.2	0.04	0.01
Basic	7.7	13.3	6.3	7.1	5.6	0.8	0.35	0.10
Intermediate	37.3	38.1	2.5	2.2	0.8	-0.3	0.02	-0.11
Advanced	89.4	87.9	0.9	1.0	-1.6	0.1	-0.01	0.07
Male 55-64								
Less than basic	1.6	2.6	1.0	1.0	1.0	0.1	0.01	0.00
Basic	5.5	9.1	3.3	4.2	3.6	0.9	0.12	0.08
Intermediate	23.2	29.5	1.1	1.2	6.3	0.1	0.07	0.02
Advanced	67.3	70.2	0.4	0.5	2.9	0.1	0.01	0.05
Male 65+								
Less than basic	1.6	1.0	0.6	0.5	-0.6	-0.1	0.00	0.00
Basic	3.2	4.9	0.9	1.2	1.8	0.3	0.02	0.01
Intermediate	9.3	10.8	0.3	0.3	1.5	0.0	0.00	0.00
Advanced	11.1	20.4	0.1	0.1	9.3	0.0	0.01	0.00
Female 15-24								
Less than basic	3.9	3.4	0.4	0.3	-0.5	-0.1	0.00	0.00
Basic	14.4	23.2	3.5	2.7	8.9	-0.8	0.31	-0.18
Intermediate	31.6	45.6	1.9	1.8	14.1	-0.1	0.26	-0.03
Advanced	59.0	61.1	0.7	0.8	2.2	0.2	0.01	0.10
Female 25-34								
Less than basic	5.2	8.0	1.4	0.8	2.8	-0.7	0.04	-0.05

	Formality rate (per cent)		Participation rate (per cent)		Change in formality rate (percentage points)	Change in participation rate (percentage points)	Coefficient effect	Composition effect
	2013Q3	2018Q3	2013Q3	2018Q3				
Basic	18.8	33.5	5.7	4.5	14.7	-1.2	0.84	-0.40
Intermediate	47.1	52.3	2.6	2.9	5.2	0.3	0.14	0.17
Advanced	88.0	84.4	2.0	2.8	-3.7	0.8	-0.07	0.64
Female 35-44								
Less than basic	4.0	9.3	2.0	1.9	5.3	-0.2	0.11	-0.01
Basic	10.7	24.5	7.3	7.0	13.9	-0.3	1.01	-0.07
Intermediate	38.8	51.4	1.7	1.6	12.6	0.0	0.21	-0.02
Advanced	92.5	92.7	1.1	1.8	0.2	0.8	0.00	0.70
Female 45-54								
Less than basic	3.7	4.4	2.1	1.9	0.8	-0.3	0.02	-0.01
Basic	6.9	13.2	6.5	6.6	6.4	0.2	0.41	0.02
Intermediate	35.3	38.1	1.5	1.6	2.8	0.0	0.04	0.01
Advanced	90.4	92.5	0.7	0.8	2.2	0.1	0.01	0.14
Female 55-64								
Less than basic	2.5	3.7	1.7	1.4	1.2	-0.2	0.02	-0.01
Basic	3.2	6.3	3.1	3.7	3.1	0.6	0.10	0.04
Intermediate	14.8	21.5	0.5	0.6	6.7	0.1	0.04	0.01
Advanced	35.9	33.7	0.1	0.2	-2.2	0.0	0.00	0.01
Female 65+								
Less than basic	1.5	1.9	1.1	0.8	0.3	-0.3	0.00	-0.01
Basic	1.3	3.4	0.8	1.0	2.0	0.2	0.02	0.01
Intermediate	8.2	9.7	0.1	0.2	1.5	0.1	0.00	0.01
Advanced	26.3	25.8	0.0	0.0	-0.5	0.0	0.00	0.00

Note: The formality rate refers to the share of formal employment in total employment. The participation rate refers to the share of workers with a certain sex, age and educational attainment in total employment.

Conclusion

This paper shows how labour force surveys, which follow a rotating panel design, can be used to extract information on labour market transitions. By highlighting the particular case of Viet Nam as an example, the paper shows that the tracking of households and their members over time can provide information on transitions along several dimensions. This includes transitions between employment, unemployment and inactivity, between formality and informality, between economic sectors, as well as between occupations. The paper relies on well-established methodologies from the literature and applies them to the particular case of Viet Nam. The applied methodologies provide the option to correct for attrition bias.

Measuring labour market transitions, or flows of workers, provides complementary information on labour market dynamics. For a comprehensive labour market analysis, aimed to provide inputs and information for evidence-based policy making, it is key to include such information. For example, an increase of formal employment could largely be driven by low exit rates from formal employment. It could, however, be also driven by high entry rates into formal employment, from informal employment or inactivity. For policy makers that wish to boost formal employment further, respective policy implications are very different.

Efforts to measure labour market transitions, or worker flows, are not new. The initial literature very much focused on developed economies and on flows into and out of unemployment. Only more recently, the literature expanded to cover also developing countries and different types of transitions, such as transitions into and out of formality. However, there are countries in which information on labour market transitions could be generated, but is not.

The number of labour market transitions that workers go through during their working lives, is expected to increase (ILO, 2019). Policy discussions around the future of work are centred around the question how to support people through these transitions. In order to build a human-centred future and "build back better" from the COVID-19 pandemic, it is key for policy makers and social partners to find good policy solutions.

As a first step, however, it is important to look at the data and learn more about these transitions. What is driving overall changes in labour market patterns? Which type of transitions are increasing over time? Which transitions play a less important role? Which workers manage to transit to more decent jobs? Which workers are stuck in less decent jobs? Which workers are stuck in informality? Which workers manage to get out of unemployment? Answers to these questions and other information derived from an analysis of labour market transitions can help inform the design of policies in support of transitions. While not aiming to be comprehensive, this paper provided a snapshot of what type of data on labour market transitions can be produced on the basis of labour force surveys that have a panel dimension. Some National Statistical Offices might wish to extend their labour market information and analysis in this direction.

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