On the Dynamics of Firm Employment

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Preliminary

March 2019

Abstract

We combine three data sources to build a unique dataset that includes detailed information about firms' employment, the work history and wages of all their workers and firm value added at a quarterly frequency for, essentially, the universe of Danish firms in 2001-2008. We show that value added is only weakly correlated with employment growth. We estimate a statistical process with permanent and transitory shocks on value added and find that transitory shocks have twice the volatility of permanent shocks. We estimate a linear and symmetric effect of permanent and transitory value added shocks on employment growth. We find that both have a statistically significant effect but only the former is economically significant: a one standard deviation positive permanent shock increases employment growth by 25% of a standard deviation. The increase in employment growth following a positive permanent shock is due to an increase in the hiring rate and a decline in the separation rate of approximately equal magnitudes, which is suggestive of a job-ladder model. Three-quarters of the increase in the hiring rate is due to higher EE inflows and one-quarter due to higher UE inflows. Approximately half of the reduction in the separation rate is due to lower EE outflows and the rest to lower EU outflows. We repeat the above exercises on ability-weighed worker flows, which we create using the worker fixed effect estimates of an AKM-type regression.

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1 Introduction

Market economies experience significant job and worker reallocation at all times: firms are continuously creating and destroying jobs and workers are constantly switching employers and employment status. The large magnitudes of job and worker reallocation have been documented in numerous studies starting with Dunne, Roberts, and Samuelson (1989) and Davis and Haltiwanger (1992) and are most commonly interpreted to be the response of firms to a variety of idiosyncratic shocks, e.g. to demand, technology, competition etc. Lack of data, however, means that there is little, if any, direct evidence systematically linking measures of firm performance to job reallocation. The present paper aims to contribute in this direction.

We combine three Danish data sources to create a unique dataset which includes detailed information about, essentially, the universe of Danish workers regarding their work history and wages, the universe of Danish firms in 2002-2008 regarding their employment and, most importantly, their value added at a quarterly frequency. This dataset is useful for a number of reasons. First and foremost, it provides with precise information on an important measure of firm performance, value added, which can be related to labor flows. Second, this information is available at high (i.e. quarterly) frequency, which is very useful for examining job and worker reallocation. Third, the information on workers is very detailed, including their daily employment history. We use this dataset to explore how value added covaries with various measures of labor flows.

Our first step is to perform a simple descriptive analysis of the value added data. We find that value added is extremely volatile: at a quarterly frequency, more than half of all firms experience (positive or negative) change in value added exceeding 30%. More importantly, value added growth correlates very weakly with employment growth, especially at high frequencies. Specifically, the correlation between them is 0.085 and 0.268 at a quarterly and annual frequency, respectively.

This observation suggests that quarterly value added is a very noisy measure of firm performance and motivates the need for a more structured empirical analysis of value added. Our second step is to estimate an empirical process for value added with transitory

and permanent shocks, following Meghir and Pistaferri (2004) and Guiso, Pistaferri, and Schivardi (2005). We find that transitory shocks are two times more volatile than permanent shocks, thereby accounting for the majority of value added volatility.

Third, we use our estimates of the value added process to estimate a linear and symmetric effect of permanent and transitory value added shocks on employment growth and other outcomes, as in Guiso, Pistaferri, and Schivardi (2005). We find that permanent shocks to value added have a statistically significant and economically meaningful effect on employment growth. Specifically, a positive 1 standard deviation permanent shock leads to an increase in the employment growth rate by 4.3 percentage points, which corresponds to 25% of employment growth's standard deviation. By contrast, a one standard deviation transitory shock has no meaningful effect on employment growth, leading to a response of half-percent of a standard deviation. These result suggest that, though value added shocks is indeed very noisy, the estimated permanent shocks do appear to capture actual shocks that are faced by firms.

Fourth, we decompose the effect of permanent value added shocks on employment growth into a hiring and a separations channel. A positive permanent shock increases employment growth through both an increase (reduction) in the hiring rate and a reduction (increase) in the separation rate, where the magnitudes of the two channels are roughly similar. This feature is consistent with a job-ladder model.

We proceed to further decompose the change in hiring according to the newly-hired worker's previous status (employed or unemployed). Following a positive permanent shock, we find that the increase in the EE hiring rate accounts for 75% of the overall increase in hiring and the increase in hiring from non-employment accounts for just 25%. By comparison, EE hires an average account for 54% of all hires, which suggests that permanent value added shocks lead to more intense poaching efforts.

Decomposing separations by the newly-separated worker's next status, we find that the EE separation rate accounts for slightly more than half (53% to be precise) of the reduction in overall separation rate following a positive and permanent value added shock. This proportion is, essentially, identical to the population share of separations that are

accounted for by EE moves (55%) which suggests that, beyond the overall reduction in the separation rate, the composition of separations is not affected by these value added shocks.

For our final exercise we run an AKM-type regression on the firm-worker panel ((Abowd, Kramarz, and Margolis, 1999)) and interpret the worker fixed effect as a measure of ability. We then weigh all the worker flows using the estimated worker abilities and repeat our previous exercises using ability-weighed worker flows. The results are comparable to those of the baseline exercise.

The rest of the paper is organized as follows. Section 2 describes the data sources and presents some summary statistics. Section 3 presents the empirical model and estimates the value added process. Section 4 presents the main results. Section 5 concludes.

2 Data

The empirical analysis is based on a comprehensive quarterly panel of all Danish firms with employment covering the period 2002Q1-2008Q3. The firm-panel is constructed from a number of Danish administrative worker- and firm-level databases, including a comprehensive matched employer-employee panel. The use of worker-level matched employer data allow us to construct ability-weighted measures of employment stocks and flows at the firm-level. This section briefly describes each of the data sources that goes into the construction of the final firm-level panel, documents the construction of the firm-level panel, and the selection of the analysis data. We end this section with some basic summary and descriptive statistics of the analysis panel.

2.1 Data sources

The analysis data is constructed from three sources: Individual-level labor market spell data, firm-level IDA data and firm-level administrative Value Added Tax (VAT) accounts. These data sources are merged by way of individual- and firm-identifiers. Individuals are identified via the social security number (CPR-number) issued to everyone residing legally

in Denmark. The social security number is unique to the individual and does not change over time. The firm identifers is constructed from firm identifiers found in the Danish Central Business Registry (the CVR) and Stamregistret for Erhvervsdrivende (the SE-registry).[1]

2.1.1 Individual-level labor market spells

The spell data contains individual job and non-employment spells. Information on job spells is available for the period January 1st, 1985 to December 31st, 2013 for all legal residents in Denmark aged 15-74, and is constructed by combining a large number of administrative registers.[2] The unit of observation in the labor market spell data is a person-spell-year. That is, a spell that stretches across three calendar years is represented by three observations. A job spell is defined as a continuous period of primary employment at a given firm, with duration measured in days.[3] A job spell observation contains information on worker and firm identifiers, start- and end-dates of the job, the annual earnings pertaining to the job, as well as an estimate of the annual number of hours worked in the job. From this we compute (an estimate of) the average annual wage rate for each year in each job.[4] Nonemployment spells are periods where no job spells are recorded. We cannot distinguish between different types of nonemployment, although (using IDA-information to be described below) we are able to discard observations pertaining to periods where a worker is in formal education for our final analysis data.

[1]The CVR was established in 1999 and contains primary data on all businesses with economic activity in Denmark, regardless of economic and organizational structure. The SE-registry was established in 1985 with the main function of identifying businesses vis-a-vis the tax authorities. At the introduction of the CVR, a business entity were typically assigned its SE-number as its new CVR-number. Using a correspondence table provided by Statistics Denmark we confirm that, at any given point in time, an SE-numbers is associated with only one CVR-number. A CVR-number may be associated with multiple SE-numbers at a given point time. The firm ID we use is constructed as part of the labor market spell data and is effectively a hybrid of the CVR- and SE-numbers. It is, however, most closely related to the CVR-number.

[2]Henning Bunzel at Aarhus University has been instrumental in constructing the labor market spell data.

[3]Primary attachment is evaluated calendar month by calendar month. For each individual in each month, the primary employer is defined as the firm at which the individual works the highest number of hours in the current and next two calendar months.

[4]Annual hours are estimated using information on mandatory pension contributions. Lund and Vejlin (2015) develop and implement a procedure for computing annual hours in a job in the IDA data for the period 1980-2007, primarily using information on mandatory pension contributions. This procedure is adapted for the spell data with some minor simplifications.

As part of an initial clean-up of the spells data, we overwrite any nonemployment spells shorter than 14 days between two job spells with different employers by back-dating the start-date of the second job spell to the day after the end-date of the first job spell. In cases where a worker ends an job spell at a firm, but returns after a period of nonemployment of no more than 12 weeks, we overwrite the nonemployment spell and instead record a single employment spell. These manipulations are intended to ensure that recall-unemployment and job-to-job transitions where start- and end-dates of the two consecutive jobs do not line up perfectly are appropriately accounted for in the empirical analysis.

2.1.2 IDA-S data

IDA-S contains annual information from public records on all physical workplaces in Denmark. We retain information on which industry a workplace belongs, aggregating IDA-S to the firm-level and defining a firm's industry to be the industry-affiliation of its largest physical workplace. Industry codes are measured using NACE codes. Our data period is long enough to stretch across several versions of the NACE taxonomy. We use an empirical correspondence table to recode earlier NACE 1.0 and NACE 1.1 codes to the newer NACE 2.0 codes. The unit of observation in the aggregated IDA-S panel is thus a firm-year.

2.1.3 VAT accounts

The VAT data is constructed from information on firms' sales and purchases obtained from administrative VAT accounts. Any firm operating in Denmark with revenue exceeding 50,000 Danish Kroner are legally obliged to obtain a VAT account with the tax authorities. The VAT account is settled monthly, quarterly or annually depending on the firm's revenue. The VAT information is contained MOMM, a monthly panel starting in January, 2001 and available up until December, 2012. We aggregate the monthly MOMM information to an quarterly frequency. For firms that settle VAT accounts on an annual frequency, the monthly information in MOMM are imputed by Statistics Denmark. We

retain an indicator for the frequency at which each firm settles their VAT accounts, and use only firms that settle their VAT accounts either monthly or quarterly in the empirical analysis. Hence, the final analysis data is not contaminated by the imputation. In this way we construct a quarterly panel with data on sales and purchases for the period 1995-2012 for the population of firms that settle VAT accounts at least quarterly. It turns out this set of firms contains almost all Danish firms with employment.

2.2 Constructing a firm-level panel

Firm-level quarterly employment is obtained from the individual-level spell data. Prior to aggregating the individual-level spell data to a firm-quarter level, we utilize the matched-employer employee data structure and the available wage-information to estimate individual ability-measures obtained as the worker fixed effects from a two-way (worker-firm) fixed effect log-wage regression. These ability measures allow us to construct ability-weighted firm-level employment, worker- and job-flows.

2.2.1 Estimating individual-level ability coefficients

Let i index individuals, and let j index firms. Furthermore, let $\mathrm{J}(i,t) = j$ if worker i is employed in firm j at time t. Now, consider the following linear model of individual log wages, $\ln w_{it}$:

$$\ln w_{it} = \theta_i + \psi_{\mathrm{J}(i,t)} + \varepsilon_{it}, \tag{1}$$

where θ_i is a worker specific effect, $\psi_{j(,i,t)}$'s are firm specific effects and ε_{it} is an i.i.d error term. Our individual-level matched employer-employee data allow us to estimate the each of the worker and firm effects using a dummy-variable regression, see e.g. Abowd, Kramarz, and Margolis (1999).[5] Notice that the dummy variable regression allow for arbitrary correlation between worker and firm fixed effects, allowing for workers to sort based on the measured firm fixed effect. We shall interpret the estimated fixed effect for worker i $\hat{\theta}_i$ as a measure of worker i's ability. In doing so, we normalize the average

[5]The log-wage regression (1) is estimated on a yearly individual-level matched employer-employee panel extracted from the spell data, including only individuals in employment on November 28th in each year.

ability in the individual-level spell data to unity.

2.2.2 Firm-level employment panel

Starting from the individual-level spell data, now containing a measure of worker-ability as outlined above, we record the number of employees, hires and separations for each firm for each quarter. Specifically, let N_{jt} be the number of worker employed in firm j at the onset of quarter t, let H_{jt} be the number of worker hired by firm j during quarter t, and finally, let S_{jt} be the number of workers separated from firm j during quarter t. A quarter-t hired worker is a worker on the payroll at the onset of quarter t, but not on the payroll at the onset of quarter $t-1$. Conversely, a quarter-t separated worker is a worker who was on the payroll at the onset of quarter $t-1$, but not on the payroll at the onset of quarter t. That is, firm-level quarterly employment N_{jt} has the following law of motion:

$$N_{jt} = N_{jt-1} + H_{jt} - S_{jt}. \tag{2}$$

A hired worker was either hired from nonemployment (i.e. made an nonemployment-to-job transition) or poached from another firm (i.e. made a job-to-job transition). Our detailed worker labor market history data allow us to distinguish between these two situations. Similarly, a separated worker either moved into nonemployment (making a job-to-nonemployment transition) or were poached by another firm (making a job-to-job transition). Hence, the following decompositions of H_{jt} and S_{jt} are given

$$H_{jt} = H_{jt}^{NJ} + H_{jt}^{JJ} \tag{3}$$

$$S_{jt} = S_{jt}^{JN} + S_{jt}^{JJ}, \tag{4}$$

where the NJ-superscripts denotes nonemployment-to-job transitions, the JJ-superscript denotes job-to-job transitions, and the JN-superscripts denotes job-to-nonemployment transitions.

Given the ability measure estimated from individual-level wage data, the law of motion for employment (2), and the decompositions (3) and (4) can computed using "ability-

weighted" employment stocks and flows. Whether ability-weighted or not, we stress that our measurement of quarterly firm-level employment dynamics is consistent with individual level employment dynamics as measured from the individual-level spell data. The firm-level panel contains (effectively) all firms with employment in Denmark during the period 1985Q1-2012Q4

2.2.3 Background information on firms

We proceed to merge our firm-level employment data with background information on the firms from IDA-S. This allow us to identify the industry in which each firm operates. The IDA-S information is available only on an annual frequency (and is aggregated from establishment-level information as detailed above), so in merging the quarterly firm-level employment panel with the IDA-S data on industry-affiliation, we implicitly assume that industry affiliation does not change within a calendar year. As we shall use industry-information at the most aggregate level, this should not pose a problem.

Next, we merge the firm-level quarterly data to the VAT accounts using the firm IDs available in both datasets. In doing so, we restrict attention to the period 2001Q1 - 2008Q3. Moreover, we restrict attention to firms that settle VAT accounts at a monthly or quarterly frequency. As it turns out, the regulations that govern the frequency at which firms settle VAT accounts is such that virtually all firms with employment settle their accounts at least quarterly. It follows that VAT data is available for virtually all firms in our firm-level employment panel. The VAT data provides measurements on each firm's sales and purchases, and therefore allow us to estimate each firm's value added at a quarterly level. The presence of firm-level value added at a quarterly frequency for the population of firms is a unique feature of our data, and one that allow us to identify the firm-level shocks of interest.

2.3 Selecting the analysis data

Based on the 2001Q1 - 2012Q4 firm we consider only the period 2001Q1 to 2008Q3 which was a period with low and stable unemployment. In addition, we restrict attention to the

Table 1: Summary statistics

Value added per hour (DKK)	247 ($50)
Average hourly wage (DKK)	184 ($32)
#Firms	47,403
Average employment	54
Average #firms/quarter	21,302
Average #workers/quarter	1,069,807
#Observations (firm-quarters)	658,579
Hiring rate, quarterly	12.4%
EE-hiring rate, quarterly	6.7%
UE-hiring rate, quarterly	5.7%
Separation rate, quarterly	11.8%
EE-separation rate, quarterly	6.6%
EU-separation rate, quarterly	5.2%

business sector, including publicly owned business firms. This selection criteria excludes public education, health services, public administration, and defence. Table 1 provides some basic summary statistics on the analysis sample.

The average value added per hour is 247DKK and the average wage per hour is 184DKK. The average firm has 54 workers and we observe approximately 21,000 every quarter. The total number of observations (firm-quarters) exceeds 650,000. The hiring rate is slightly higher than the separation rate over the time period 2001Q1:2008Q3, during which the unemployment rate dropped from 4.4% to 3.6%. Approximately 55% of both rates is accounted for by job-to-job transitions and the rest by movement to/from non-employment.

Figure 1 shows the distribution of quarterly and annual value added growth rates (top left and top right panel, respectively) and employment growth rates (bottom left and bottom right panel, respectively). Table 2 tabulates the distribution of value added and employment growth rates, and also provides the contemporaneous firm-level correlation between value added growth and employment growth at quarterly frequency. Table 3 provies the same statistics, but on an annual frequency.

Figure 1: Distribution of quarterly and annual growth rates of value added and employment

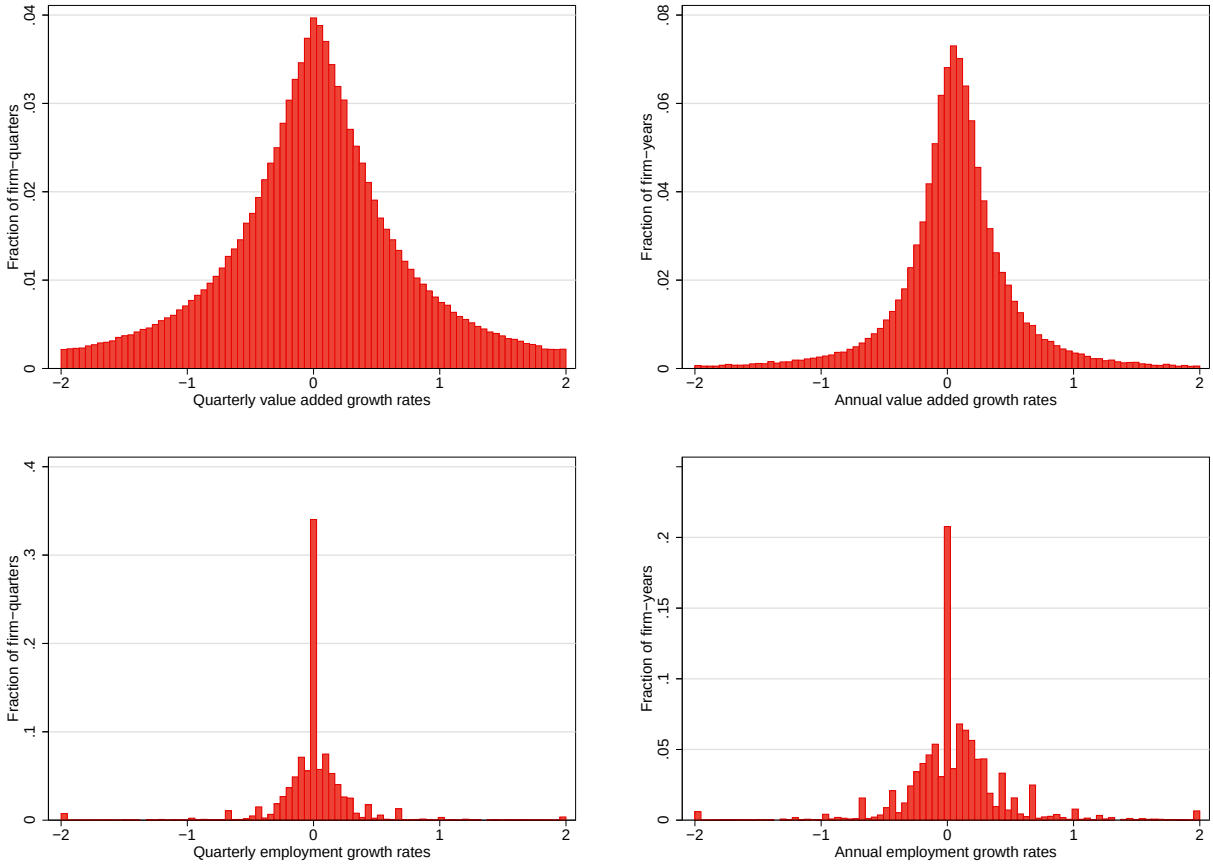


Table 2: Quarterly value added and employment growth rates

	$\Delta \log y_{jt}$	$\Delta \log N_{jt}$
Average	0.009	0.006
Std. Dev.	0.863	0.158
10th percentile	-0.843	-0.134
25th percentile	-0.335	-0.061
50th percentile	0.013	0.000
75th percentile	0.359	0.069
90th percentile	0.840	0.148
Correlation matrix	$\Delta \log y_{jt}$	$\Delta \log N_{jt}$
$\Delta \log y_{jt}$	1.000	
$\Delta \log N_{jt}$	0.085	1.000

Table 3: Annual value added and employment growth rates

	$\Delta \log y_{jt}$	$\Delta \log N_{jt}$
Average	0.007	0.011
Std. Dev.	0.581	0.192
10th percentile	-0.493	-0.162
25th percentile	-0.156	-0.067
50th percentile	0.038	0.012
75th percentile	0.217	0.093
90th percentile	0.478	0.190
Correlation matrix	$\Delta \log y_{jt}$	$\Delta \log N_{jt}$
$\Delta \log y_{jt}$	1.000	
$\Delta \log N_{jt}$	0.239	1.000

With respect to value added we note a substantial amount of variation. Indeed, in our raw data, while not a common occurrence, there is a surprising amount of mass in the tails of the distribution. Indeed, 50% of the firm-quarters in our data, face value added growth in excess of ±40%. At an annual frequency, this is of course much less common, but do nonetheless occur (see Table 3). Taken at face value, the evidence in the top panel of Figure 1 and the left column of Table 2 leaves open the possibility that firms in our data face substantial value added shocks. Looking now at the bottom panel of Figure 1 and the right column of Table 2, we note that employment growth rates also exhibits considerable dispersion across firm-quarters, albeit with a large mass-point at zero growth. This is in line with existing evidence from the US, see e.g. Davis, Faberman, and Haltiwanger (2012). Finally, we note that the contemporaneous correlation between value added growth and employment growth is positive, but small at 0.085. This correlation increases substantially to 0.239 when we consider annual growth rates in Table 3. The next section sets up a rich empirical model of the value added shock process and employment adjustment to rigorously investigate how firm-level shocks to value added may drive firm-level employment dynamics.

3 Empirical model of value added

3.1 Value added shocks

Following Guiso, Pistaferri, and Schivardi (2005) we stipulate the following dynamic process for quarterly firm-level value added:

$$\varrho(L) \ln Y_{jt} = \mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j + \epsilon_{jt}. \tag{5}$$

Here, $\varrho(L)$ is a lag-polynomial that captures pre-determined variation in value added, reflecting pre-committed sales and other predictable shocks to firm-level value added, $\mathbf{X}_{jt}$ is a vector strictly exogenous covariates, which in our case consist of industry dummies and industry-specific time-trends, η_j is a firm fixed effect, and ϵ_{jt} represent the "true" value added shock. Our interest centers on the shock process ϵ_{jt}, which needs to be estimated from residuals after the unknown parameters in (5) has been estimated.

To proceed, we shall assume that the value added shock process follows an $ARIMA(0, 1, q)$-process, i.e contains a unit root process and as well as an MA-process. Formally,

$$\epsilon_{jt} = u_{jt} + \vartheta(L)\tilde{\nu}_{jt}, \tag{6}$$

and

$$u_{jt} = u_{jt-1} + \tilde{\omega}_{jt}. \tag{7}$$

Here, $\tilde{v}_{jt}$ is the innovation to the MA-component and $\tilde{\omega}_{jt}$ is the innovation to the unit root process. $\vartheta(L)$ is an order-q lag-polynomial.

The firm fixed effect in (5) is a nuisance parameter, but a simple difference transformation of (5) rids the model of η_j, and equation (5), now describing quarterly value added growth at the firm-level, becomes

$$\varrho(L)\Delta \ln Y_{jt} = \Delta\mathbf{X}_{jt}\boldsymbol{\gamma} + \Delta\epsilon_{jt}, \tag{8}$$

Table 4: Estimated value added process

log VA, lagged 1 quarter	−0.288	(0.028)
log VA, lagged 2 quarters	−0.292	(0.027)
log VA, lagged 3 quarters	−0.285	(0.027)
log VA, lagged 4 quarters	0.667	(0.027)
Arrelano-Bond test (autocov, order 5)	22.13	[0.000]
Arrelano-Bond test (autocov, order 6)	−2.33	[0.020]
Arrelano-Bond test (autocov, order 7)	1.74	[0.082]
Overidentifying restriction test	27.74	[0.148]
Number of observations	556,736	
Number of firms	32,571	

Note: Dependent variable is log VA. We use log VA lagged 6 or more quarters as instruments in a DIF-GMM regression. The regression includes year dummies and industry-specific trends. Standard errors in parentheses. P-values in square brackets.

where

$$\Delta\epsilon_{jt} = \tilde{\omega}_{jt} + \vartheta(L)\Delta\tilde{\nu}_{jt}, \tag{9}$$

In the absence of lagged dependent variables, (8) can be estimated by OLS to obtain estimates of the residual value added growth. In the presence of lagged dependent variables, however, OLS yields inconsistent parameter estimates, and therefore generates inconsistent residuals. Instead, (8) can be estimated by a GMM regression using Arellano-Bond type instruments, see Arellano and Bond (1991). The resulting estimator, sometimes referred to as a difference-GMM, or DIF-GMM, estimator yields consistent estimates of $\Delta\epsilon_{jt}$, a central component of the analysis to come.

Table 4 presents out preferred DIF-GMM estimates of the value added process. This specification passes the test for overidentifying restrictions, or instrument validity. The specification include 4 lags of deterministic dynamics in y_{jt} and a first-differenced error-term $\Delta\epsilon_{jt}$ with an autocovariance process that resembles an $MA(5)$ process. The process estimated value added process is stationary. Table 5 tabulates the autocovariances of residual log value added

As mentioned, the empirical autocovariances presented in Table 5 are consistent with an $MA(5)$ process for $\Delta\epsilon_{jt}$, which would imply a unit root process plus an $MA(4)$ process

Table 5: Residual log value added autocovariances

Order 0	0.989	(0.010)	[0.000]
Order 1	−0.447	(0.006)	[0.000]
Order 2	0.013	(0.004)	[0.001]
Order 3	0.200	(0.005)	[0.000]
Order 4	−0.387	(0.007)	[0.000]
Order 5	0.181	(0.005)	[0.000]
Order 6	−0.002	(0.004)	[0.630]
Order 7	−0.004	(0.005)	[0.434]
Order 8	−0.003	(0.005)	[0.521]
Order 9	0.008	(0.005)	[0.091]
Order 10	−0.010	(0.005)	[0.066]
Order 11	−0.003	(0.005)	[0.524]
Order 12	0.000	(0.005)	[0.984]
Order 13	0.000	(0.005)	[0.960]
Order 14	0.003	(0.006)	[0.568]

Note: Standard errors in brackets. P-values in square brackets.

for ϵ_{jt} would fit the data. In fact, we can estimate the parameters of such a process using the implied restrictions on the autocovariance process in a Minimum Distance Estimator. Table 6 presents the resulting parameter estimates.

We note that the $MA(4)$ model provides a good fit to the data. Moreover, we note that the variance in the transitory innovations is an order of magnitude larger than the variance to the permanent innovations. This result is important, and will help us interpret some of other empirical findings to come.

Table 6: Residual log value added autocovariances

Std dev of permanent innovation, σ_u	0.152	(0.001)
Std dev of transitory innovation, σ_v	0.358	(0.001)
MA(1) coefficient, θ_1	0.494	(0.003)
MA(2) coefficient, θ_2	0.274	(0.004)
MA(3) coefficient, θ_3	0.377	(0.004)
MA(4) coefficient, θ_4	1.052	(0.006)
EWMD objective function value	3.652×10^{-6}	

Note: Standard errors in parentheses.

3.2 Permanent and transitory value added shocks

Following Guiso, Pistaferri, and Schivardi (2005) we provide a useful interpretation of the estimated residual value added process as consisting of a permanent and a transitory component.

First, we show that $\ln Y_{jt}$ and u_{jt} are co-integrated. Indeed, letting $\varrho(L) = 1 - \rho_1 L - \rho_2 L^2 - ... - \rho_p L^p$, straightforward algebra reveals that the value added process (5) has the following error correction representation:

$$\Delta \ln Y_{jt} = \mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j - \rho_1^* \Delta \ln Y_{jt-1} - \rho_2^* \Delta \ln Y_{jt-2} - ... - \rho_{p-1}^* \Delta \ln Y_{jt-p+1} \\ - \varrho(1)\left[\ln Y_{jt-1} - \varrho(1)^{-1} u_{jt-1}\right] + \vartheta(L)\tilde{v}_{jt} + \tilde{\omega}_{jt},$$

where $\rho_k^* = -\sum_{s=k+1}^{p} \rho_s$ is a composite parameter.

It follows from Granger's Representation Theorem that $\ln Y_{jt}$ and u_{jt} are co-integrated with co-integrating vector $(1, -\varrho(1)^{-1})'$. We therefore interpret $\varrho(1)^{-1} u_{jt}$ as the stochastic (long run) trend for $\ln Y_{jt}$. Firm-level log value added innovations shift $\varrho(1)^{-1} u_{jt}$ around. We can interpret these shifts as permanent shocks to a firm's log value added because it shifts the stochastic trend for that firm's value added process.

With this result in mind, go back to the equation in levels and rewrite it (by multiplying through by $\varrho(L)^{-1}$, and adding and subtracting $\varrho(1)^{-1} u_{jt}$) as

$$\ln Y_{jt} = \varrho(L)^{-1}\left[\mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j\right] + \varrho(1)^{-1} u_{jt} + \left\{\varrho(L)^{-1}\left[u_{jt} + \vartheta(L)\tilde{\nu}\right] - \varrho(1)^{-1} u_{jt}\right\}. \quad (10)$$

Equation (10) decomposes $\ln Y_{jt}$ into the long-run expected trend of firm j's (log) value added $\varrho(L)^{-1}\left[\mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j\right] + \varrho(1)^{-1} u_{jt}$, with a deterministic and a stochastic component, and transitory deviations from the trend $\varrho(L)^{-1}\left[u_{jt} + \vartheta(L)\tilde{\nu}\right] - \varrho(1)^{-1} u_{jt}$. Further ma-

nipulation on (10) yields the following expression[6]

$$\ln Y_{jt} = \varrho(L)^{-1}\Big[\mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j\Big] + \varrho(1)^{-1}u_{jt} + \varrho(L)^{-1}\Big[\vartheta(L)\tilde{\nu} + (1-L)^{-1}[1-\varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}\Big]. \tag{11}$$

It is now natural to decompose observed log value added according to

$$\ln Y_{jt} = D_{jt} + P_{jt} + T_{jt},$$

where

$$D_{jt} \equiv \varrho(L)^{-1}\Big[\mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j\Big],$$

is a *deterministic* component,

$$P_{jt} \equiv \varrho(1)^{-1}u_{jt},$$

is a *permanent* (i.e. long run) component, and

$$T_{jt} \equiv \varrho(L)^{-1}\Big[\vartheta(L)\tilde{\nu}_{jt} + (1-L)^{-1}[1-\varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}\Big],$$

is a *transitory* (short run) component.

In first differences, i.e. considering log value added growth, we have

$$\Delta \ln Y_{jt} = \Delta D_{jt} + \Delta P_{jt} + \Delta T_{jt},$$

where

$$\Delta D_{jt} = \varrho(L)^{-1}\Delta\mathbf{X}_{jt}\boldsymbol{\gamma},$$

is a deterministic component,

$$\Delta P_{jt} = \varrho(1)^{-1}\tilde{\omega}_{jt} \equiv \omega_{jt},$$

[6]Note that, if we set $\varrho = 1-\rho L$ and $\vartheta(L) = 1-\theta L$ as in Guiso, Pistaferri, and Schivardi (2005), our expression (11) simplifies to theirs:

$$\ln Y_{jt} = (1-\rho L)^{-1}\Big[\mathbf{X}_{jt}\boldsymbol{\gamma} + \eta_j\Big] + (1-\rho)^{-1}u_{jt} + (1-\rho L)^{-1}\Big[(1-\theta L)\tilde{\nu} - (1-\rho)^{-1}\rho\tilde{\omega}_{jt}\Big].$$

is a permanent (long run) component, and

$$\Delta T_{jt} = \varrho(L)^{-1}\left[\vartheta(L)\Delta\tilde{\nu}_{jt} + [1 - \varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}\right] \equiv \varrho(L)^{-1}\Delta\nu_{jt},$$

is a transitory (short run) component.

Finally, for future reference, notice that the first differenced residuals from the GMM value added regression are

$$\Delta\epsilon_{jt} = \varrho(L)\Delta \ln Y_{jt} - \Delta\mathbf{X}_{jt}\boldsymbol{\gamma} = \varrho(L)\Delta P_{jt} + \varrho(L)\Delta T_{jt} = \varrho(L)\omega_{jt} + \Delta\nu_{jt},$$

which may also be written in terms of the fundamental innovations $\tilde{\omega}_{jt}$ and $\tilde{\nu}_{jt}$ as

$$\Delta\epsilon_{jt} = \varrho(L)\varrho(1)^{-1}\tilde{\omega}_{jt} + \vartheta(L)\Delta\tilde{\nu}_{jt} + [1 - \varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt} = \vartheta(L)\Delta\tilde{\nu}_{jt} + \tilde{\omega}_{jt}.$$

3.3 Firm-level employment dynamics and value added shocks

We model firm-level employment N_{jt} as

$$\ln N_{jt} = \mathbf{X}_{jt}\tilde{\boldsymbol{\eta}} + \phi_j + \alpha P_{jt} + \beta T_{jt} + \chi D_{jt} + \tilde{\psi}_{jt}, \tag{12}$$

where

$$\tilde{\psi}_{jt} = z_{jt} + \zeta(L)\xi_{jt}, \tag{13}$$

and

$$z_{jt} = z_{jt-1} + \mu_{jt}. \tag{14}$$

Hence, firm-level employment net of the effect of a set of strictly exogenous variables, containing industry dummies and time trends, and a firm fixed effect ϕ_j, depends on the firm-level value added process $\ln Y_{jt} = D_{jt} + P_{jt} + T_{jt}$ as well as a separate stochastic process $\tilde{\psi}_{jt}$ that shifts employment independently of trends and value added shocks. We allow permanent and transitory value added shocks to have separate effects on employment. The differential impact are measured by the loading coefficients α and β. The

effect of the deterministic trend in value added on employment is measured by the loading factor χ. Guiso, Pistaferri, and Schivardi (2005) use a similar formulation study the extent to which permanent and transitory shocks are passed into workers' wages. Here, we consider instead how different shocks impact employment and employment dynamics.

To proceed, take first differences and multiply by $\varrho(L)$ (a known object, from the value added regression) and substitute in $\varrho(L)\Delta D_{jt} = \Delta \mathbf{X}_{jt}\boldsymbol{\gamma}$ to get

$$\varrho(L)\Delta \ln N_{jt} = \varrho(L)\Delta \mathbf{X}_{jt}\tilde{\boldsymbol{\eta}} + \chi\Delta \mathbf{X}_{jt}\boldsymbol{\gamma} + \alpha\varrho(L)\Delta P_{jt} + \beta\varrho(L)\Delta T_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt},$$

and defining $\boldsymbol{\eta} = \tilde{\boldsymbol{\eta}} + \chi\boldsymbol{\gamma}$ we can write

$$\varrho(L)\Delta \ln N_{jt} = \varrho(L)\Delta \mathbf{X}_{jt}\boldsymbol{\eta} + \alpha\varrho(L)\Delta P_{jt} + \beta\varrho(L)\Delta T_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt}.$$

Next, defining $\Delta\psi_{jt} \equiv \alpha\varrho(L)\Delta P_{jt} + \beta\varrho(L)\Delta T_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt}$, $\ln \tilde{N}_{jt} \equiv \varrho(L)\ln N_{jt}$ and $\tilde{\mathbf{X}}_{jt} \equiv \varrho(L)\mathbf{X}_{jt}$, we have

$$\Delta \ln \tilde{N}_{jt} = \Delta \tilde{\mathbf{X}}_{jt}\boldsymbol{\eta} + \Delta\psi_{jt}$$

A consistent estimate of $\boldsymbol{\eta}$, and hence of $\Delta\psi_{jt}$, our real object of interest, can be obtained by OLS.

To see this, let $\boldsymbol{\Omega}_j$ be the variance-covariance matrix of $\Delta\psi_{jt}$ for firm j, and let $\boldsymbol{\Omega}$ be variance-covariance matrix for the sample, a block-diagonal matrix with $\boldsymbol{\Omega}_j$ along the diagonal (the $\boldsymbol{\Omega}$ thus reflects that $\Delta\psi_{jt}$ are uncorrelated across j, but leaves the correlation across t, i.e. the autocorrelation, completely unrestricted within each firm). Furthermore, let $\Delta \ln \tilde{\boldsymbol{N}}_j$ be the vector of employment growth for firm j, and let $\Delta \ln \tilde{\boldsymbol{N}}$ contain the stacked $\Delta \ln \tilde{\boldsymbol{N}}_j$, and the same for $\Delta\tilde{\mathbf{X}}_j$ and $\Delta\tilde{\mathbf{X}}$. The OLS estimator of $\boldsymbol{\eta}$ is

$$\hat{\boldsymbol{\eta}}_{OLS} = (\Delta\tilde{\mathbf{X}}'\Delta\tilde{\mathbf{X}})^{-1}\Delta\tilde{\mathbf{X}}'\Delta \ln \tilde{\boldsymbol{N}} = \boldsymbol{\eta} + (\Delta\tilde{\mathbf{X}}'\Delta\tilde{\mathbf{X}})^{-1}\Delta\tilde{\mathbf{X}}'\Delta\boldsymbol{\psi},$$

where $\boldsymbol{\psi}$ contain the stacked employment innovations. Assuming $\operatorname{plim}\Delta\tilde{\mathbf{X}}'\Delta\tilde{\mathbf{X}} = \mathbf{Q}$ (some non-stochastic matrix with full column rank), the maintained assumptions on the the innovations ψ_{jt} is that they are orthogonal to the elements in the deterministic

component $\Delta\tilde{\mathbf{X}}$. That is, plim $\Delta\tilde{\mathbf{X}}'\Delta\boldsymbol{\psi} = \mathbf{0}$. It follows that

$$\text{plim}\,\hat{\boldsymbol{\eta}}_{OLS} = \boldsymbol{\eta}.$$

We do not report the estimated employment regressions as these are of limited interest in and off themselves. The next section, however, makes heavy use of the residuals from the employment regression to identify the loading coefficients α and β in (12).

Finally, for future reference, recall that

$$\Delta\psi_{jt} = \alpha\varrho(L)\Delta P_{jt} + \beta\varrho(L)\Delta T_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt} = \alpha\varrho(L)\omega_{jt} + \beta\Delta\nu_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt},$$

which may be expressed in terms of the underlying innovations,

$$\Delta\psi_{jt} = \alpha\varrho(L)\varrho(1)^{-1}\tilde{\omega}_{jt} + \beta\Big[\vartheta(L)\Delta\tilde{\nu}_{jt} + [1 - \varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}\Big] + \varrho(L)\Delta\tilde{\psi}_{jt}.$$

3.4 Estimation of α and β

The objects of primary interest in the empirical model described above are the loading coefficients α and β that captures the employment response to permanent and transitory value added shocks, respectively. Here, following Guiso, Pistaferri, and Schivardi (2005) we detail how these parameters may be identified from the value added and employment residuals.

Take $\Delta\epsilon_{jt}$, the residuals from the value added regression, and multiply by $\beta\varrho(L)$ to obtain

$$\beta\Delta\epsilon_{jt} = \beta\varrho(L)\omega_{jt} + \beta\Delta\nu_{jt},$$

and subtract it from $\Delta\psi_{jt}$ to get

$$\Delta\psi_{jt} - \beta\Delta\epsilon_{jt} = [\alpha - \beta]\varrho(L)\omega_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt} = [\alpha - \beta]\varrho(L)\varrho(1)^{-1}\tilde{\omega}_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt}$$

Multiply by $\Delta\epsilon_{jt+1}$ and consider the expectation across time and firms,

$$\mathrm{E}\Big[\Delta\epsilon_{jt+1}(\Delta\psi_{jt} - \beta\Delta\epsilon_{jt})\Big].$$

Since $\Delta\epsilon_{jt+1} = \vartheta(L)\Delta\tilde{\nu}_{jt+1} + \tilde{\omega}_{jt+1}$ we have

$$\mathrm{E}\Big[\Delta\epsilon_{jt+1}(\Delta\psi_{jt}-\beta\Delta\epsilon_{jt})\Big] = \mathrm{E}\Big[(\vartheta(L)\Delta\tilde{\nu}_{jt+1}+\tilde{\omega}_{jt+1})([\alpha-\beta]\varrho(L)\varrho(1)^{-1}\tilde{\omega}_{jt}+\varrho(L)\Delta\tilde{\psi}_{jt})\Big] = 0.$$

It follows that the orthogonality condition $\mathrm{E}\big[\Delta\epsilon_{jt+1}(\Delta\psi_{jt} - \beta\Delta\epsilon_{jt})\big] = 0$ identifies β, the loading parameter on the transitory value added shocks in the employment equation. The orthogonality condition is straightforward to operationalize through an instrumental variable regression of $\Delta\psi_{jt}$, the employment equation residuals, onto $\Delta\epsilon_{jt}$, the value added equation residuals, using $\Delta\epsilon_{jt+1}$, the leaded value added residuals, as an instrumental variable.

To identify α, the loading coefficient on the permanent value added shocks in the employment equation, take $\alpha\Delta\epsilon_{jt}$ and subtract it from $\Delta\psi_{jt}$

$$\Delta\psi_{jt} - \alpha\Delta\epsilon_{jt} = [\beta - \alpha]\Delta\nu_{jt} + \varrho(L)\Delta\tilde{\psi}_{jt}$$

which we may express as

$$\Delta\psi_{jt} - \alpha\Delta\epsilon_{jt} = [\beta - \alpha][\vartheta(L)\Delta\tilde{\nu}_{jt} + [1 - \varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}] + \varrho(L)\Delta\tilde{\psi}_{jt}.$$

Now consider the moment, as in Meghir and Pistaferri (2004):

$$\begin{aligned}
&\mathrm{E}\Big[\Big(\sum_{s=-5}^{5}\Delta\epsilon_{jt+s}\Big)(\Delta\psi_{jt} - \alpha\Delta\epsilon_{jt})\Big] \\
&= \mathrm{E}\Big[\Big(\sum_{s=-5}^{5}[\vartheta(L)\Delta\tilde{\nu}_{jt+s}+\tilde{\omega}_{jt+s}]\Big)([\beta-\alpha][\vartheta(L)\Delta\tilde{\nu}_{jt}+[1-\varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}]+\varrho(L)\Delta\tilde{\psi}_{jt})\Big].
\end{aligned}$$

As it turns out,[7]

$$\mathrm{E}\Big[\Big(\sum_{s=-5}^{5}\Delta\epsilon_{jt+s}\Big)(\Delta\psi_{jt}-\alpha\Delta\epsilon_{jt})\Big]$$
$$=\mathrm{E}\Big[\Big(\sum_{s=-5}^{5}[\vartheta(L)\Delta\tilde{\nu}_{jt+s}+\tilde{\omega}_{jt+s}]\Big)([\beta-\alpha][\vartheta(L)\Delta\tilde{\nu}_{jt}+[1-\varrho(L)\varrho(1)^{-1}]\tilde{\omega}_{jt}]+\varrho(L)\Delta\tilde{\psi}_{jt})\Big]=0$$

This moment condition is also straightforward to operationalize using an instrumental variable regression approach.

4 Employment dynamics and value added shocks

This section presents our main results, relating to the transmission of firm-level value added shocks to firm-level employment adjustments at a quarterly frequency. We present three sets of results. First, we consider the transmission of value added shocks onto employment. Next, decompose the employment effect into the effect of hiring and separation rates.[8] Here, we are also able to split hiring and separations into NJ-, JJ-, and JN-transitions, according to (3) and (4). Finally, we redo the empirical analysis on employment adjustment, hiring and separations using ability weighted worker flows, see (1).

[7] Suppose that $\vartheta(L)\Delta\tilde{\nu}_{jt+s}$ is an MA-process of order 5. Hence

$$\mathrm{E}\Big[\Big(\sum_{s=-5}^{5}\vartheta(L)\Delta\tilde{\nu}_{jt+s}\Big)\vartheta(L)\Delta\tilde{\nu}_{jt}\Big]=0$$

In addition,

$$\mathrm{E}\Big[\Big(\sum_{s=-5}^{5}\tilde{\omega}_{jt+s}\Big)\tilde{\omega}_{jt}\Big]=\mathrm{Var}(\tilde{\omega}_{jt})$$

and

$$-\varrho(1)^{-1}\mathrm{E}\Big[\Big(\sum_{s=-5}^{5}\tilde{\omega}_{jt+s}\Big)\varrho(L)\tilde{\omega}_{jt}]\Big]=-\varrho(1)^{-1}\varrho(1)\mathrm{Var}(\tilde{\omega}_{jt})=-\mathrm{Var}(\tilde{\omega}_{jt}).$$

[8] In doing so, it is not necessary to first difference the hiring and separation equations. There can be no firm fixed effect in hiring and separation decisions.

Table 7: Transmission of value added shocks into employment

	Permanent		Transitory	
Loading factors (α_N, β_N)	0.345	(0.035)	−0.005	(0.001)
Weak instruments	41.927	[0.000]	8,513.45	[0.000]
Overidentifying restrictions	5.014	[0.082]	1.047	[0.593]
Exogeneity test	329.143	[0.000]	404.77	[0.000]
Observations	122,240		294,911	

Note: Standard errors in parentheses. P-values in square brackets.

4.1 Employment dynamics

Table 7 presents the first set of result relating to the transmission of value added shocks into firm-level employment adjustment. As described above, we are particularly interested in estimating potentially different impacts of permanent value added shocks (shifting a firm's long run value added trend) and transitory shocks that represent deviations from the long run trend. The first column in Table 7 presents the estimated loading coefficient on the permanent shock in the employment equation. The second column presents the estimated loading coefficient on the transitory shock. As also described above, the orthogonality conditions that identify the loading factors can be operationalized using simple instrumental variable regressions, and Table 7 also presents standard diagnostic tests for weak instruments, overidentifying restrictions, and exogeneity, derived from these instrumental variable regressions.

Turning now to the content of Table 7, we note first of all that the instrumental variable regressions pass the reported standard diagnostic tests. With respect to the estimated loading factors, an interesting result emerge: Permanent shocks have a statistically significant and economically meaningful impact on employment growth. Indeed, from Table 6 we note that a one standard deviation permanent shock is 0.15, and the loading coefficient reported in Table 7 implies that such a shock would, increase the employment growth rate by 0.043, about a quarter of a standard deviation in the distribution of employment growth rates. This is an economically significant effect.

In contrast, the parameter estimate on the loading coefficient on the transitory value

added shocks in Table 7 shows that the effect of these shocks on employment growth, though statistically significant, is economically extremely small. The point estimates in Table 7 implies that a one standard deviation transitory shock to value added lead to a 0.001 reduction in the employment growth rate, or approximately half of one percent of a standard deviation in the distribution of employment growth rates.

4.2 Employment dynamics by transition type

Our data is sufficiently rich that we can separate variation in employment growth rates coming from transitions into and out of unemployment from transitions between firms. In Table 8 we decompose the impact of permanent value added shocks on the employment growth rate into effects running through the hiring rate and the separation rate. Furthermore, we decompose the hiring margin into an EE and an UE margin, and the separation maring into an EE and EU margin.

An interesting pattern emerge from Table 8, whereby the hiring maring appears slightly more responsive to shocks than the separation margins, but both margins respond in the wake of a permanent shock to value added. We noted above that the overall loading coefficient of 0.35 implies that a one standard deviation permanent shock to value added increases the employment growth rate by 4.3 percentage points. The estimates reported in Table 8 implies that this overall increase is obtained through an increase in the hiring rate of about 2.5 percentage point and a drop in the separation rate of 1.7 percentage points.

The 2.5 percentage point increase in the hiring rate following a one standard deviation permanent shock to value added can be realized by firms increasing the rate at which they poach workers, i.e. hiring through EE transitions, or the rate at which they hire from unemployment, i.e. hire through UE transitions. The estimates reported in Table 8 implies that approximately 75% of hires are accounted for by increased poaching with the remainder coming through increased hiring from the unemployment pool.

Similarly, the 1.7 percentage point reduction in the separation rate following a one standard deviation permanent shock to value added can be achieved by an reducing the

Table 8: Transmission of value added shocks into employment: Decomposing by transition type

	α_Z
Employment growth	0.345 (0.035)
Hiring rate	0.201 (0.024)
EE hiring rate	0.154 (0.017)
UE hiring rate	0.047 (0.011)
Separation rate	-0.141 (0.020)
EE separation rate	-0.075 (0.012)
EU separation rate	-0.066 (0.011)

Note: Standard errors in parentheses.

rate at which workers quit the firm for employment at other firms, i.e. through EE separations, or by reducing the rate at worker are laid off, i.e. are making EU transitions. The estimates reported in Table 8 implies that 55% of the 1.7 percentage point reduction in the separation rate are accounted for by a reduced quit rates with the remainder coming through reduced rates of layoffs.

In summary, permanent value added shock has statistically significant and economically meaningful impact on the employment growth rate. Hiring rates seem slightly more responsive than separation rates, and firms tend to adjust hiring and separation rates along the quit margin.

4.3 Ability weighted employment dynamics

Using the estimated ability coefficients obtained from an individual level wage regression , see (1), we can redo the whole analysis conducted above with ability weighted employment stocks and flows. Effectively, we interpret the worker fixed effect as a measure of ability and weigh all the worker stock and flows using the estimated worker abilities. The results of this analysis are presented in Table 9 which, for comparison, also contains the results from Table 8.

We find that the effect of a permanent value added shock on ability-weighed hiring

Table 9: Transmission of value added shocks into ability-weighted employment

	$\Delta \log N_{jt}$	$\Delta \log \hat{N}_{jt}$
Average	0.006	0.005
Standard deviation	0.158	0.150
10th percentile	-0.134	-0.118
25th percentile	-0.061	-0.050
50th percentile	0.000	0.000
75th percentile	0.069	0.057
90th percentile	0.148	0.131

and separation rates is almost twice as large than on the unweighed rates. In other words, high-ability workers are affected by permanent value added shocks to a much larger extent than low-ability workers. This suggests that focusing on the number of workers who are reallocated seriously underestimated the reallocation of productive capacity, which is properly measured by appropriately controlling for the type composition of movers and stayers.

4.4 Value added shocks and vacancy postings

Table 10 reports how permanent and transitory value added shock are transmitted into vacancy postings, which we here take to be the probability that firm posts at least one vacancy during the quarter. We find that permanent shocks are positively and significantly related to the probability of posting a vacancy while transitory shocks are uncorrelated with vacancy postings. These result suggest that, though transitory value added shocks are indeed very noisy, the estimated permanent shocks appear to capture actual shocks that are faced by firms.

5 Conclusion

In this paper we have combined three data sources to build a unique and comprehensive dataset that includes detailed information about firms' employment, the work history and

Table 10: Value added shocks and the probability of posting a vacancy

	"raw"	ability-weighed
Employment growth	0.345	0.327 (0.033)
Hiring rate	0.201	0.208 (0.024)
EE hiring rate	0.154	0.157 (0.017)
UE hiring rate	0.047	0.050 (0.011)
Separation rate	-0.141	-0.115 (0.017)
EE separation rate	-0.075	-0.058 (0.011)
EU separation rate	-0.066	-0.056 (0.010)

Note: Standard errors in parentheses.

wages of all their workers, value added at a quarterly frequency and vacancy postings for, essentially, the universe of Danish firms in 2002-2008. We use this data to estimate a statistical process characterizing firm-level value added. Specifically, our specification features permanent and transitory shocks to value added. We find that permanent value added shocks are significantly related to employment growth but transitory shocks are uncorrelated with employment growth. Permanent shocks affect employment growth both through the hiring and the separation rate, and the effect on the poaching rate is two times greater than on the transition rates to and from unemployment.

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