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Productivity, Efficiency and Labor Reallocation

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Productivity, Efficiency and Labor Reallocation*

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Abstract

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1 Introduction

In this paper we study labor reallocation and relate this to productivity growth.

This paper is organized as follows: Section (2) outlines the theory underlying the decomposition of TFP we rely on. Section (3) discusses the method and the data. Section (4) reports the results. Finally, section (5) concludes.

2 Theory

3 Method and Data

Methodology

In this section we outline the empirical method used to study labor reallocation effects on productivity. In terms of Basu and Fernald (2002), the term we are interested in measuring is

$$R_{Lt} = \sum_{j=1}^{J_t} \omega_{jt} s_{Ljt}^{V} \left[\frac{P_{Ljt} - P_{Lt}}{P_{Ljt}} \right] dl_{jt}, \tag{1}$$

where J_t denotes the total number of firms in the economy at time t, ω_{jt} is the firm's share in aggregate nominal value added at time t, s_{Ljt}^{V} is the firm's share of labor costs in nominal value added at time t and dl_{jt} is the firm's growth rate of labor input. Moreover, P_{Ljt} is the price of a unit of homogenous labor paid by firm j, and P_{Lt} is the market price for the same factor.

Since there is no directly observable counterpart to the market price of a unit of homogenous labor or to the price paid by the individual firm, we need to resort to econometric methods. Here, we rely on a two-way fixed-effects model, along the lines of Abowd, Kramarz, and Margolis (1999), to construct measures of these objects. The specification we take to the data is

$$\ln w_{ijt} = \gamma_j + \gamma_i + \sum_{p=1}^{P} \lambda_p age_{ijt}^{p} + \lambda_t + \varepsilon_{ijt}, \tag{2}$$

where w_{ijt} is the (nominal) wage for worker i at firm j at time t, γ_j denotes a firm j fixed effect, γ_i is a worker i fixed effect and ε_{ijt} is a stochastic error. We also introduce an age polynomial, $\sum_{p=1}^{P} \lambda_p age_{ijt}^{p}$, and time effects (including an overall constant), λ_t. Note that we can rewrite equation (1) as

$$R_{Lt} = \sum_{j=1}^{J_t} \omega_{jt} s_{Ljt}^{V} \left[1 - e^{\ln(P_{Lt}/P_{Ljt})}\right] dl_{jt}. \tag{3}$$

From an estimate of (2) we can obtain a measure of the log difference between the firm-specific pay of an homogenous worker and the market price. Let I_{jt} denote the number of workers employed at firm j at time t, and define

$$\widehat{\ln \frac{P_{Lt}}{P_{Ljt}}} = \widehat{\ln \frac{P_{L}}{P_{Lj}}} = \frac{1}{\left(\sum_{t=1}^{T} \sum_{j=1}^{J_t} I_{jt}\right)} \sum_{t=1}^{T} \sum_{j=1}^{J_t} I_{jt} \hat{\gamma}_j - \hat{\gamma}_j, \tag{4}$$

where T is the final year of observation in the sample. Our measure is thus defined as the difference between the average firm effect across employees and years and the firm fixed effect. Note that this measure will be time invariant.[1] One issue is wether one should include the firm average of the residual $\frac{1}{I_{jt}} \sum_{i=1}^{I_{jt}} \hat{\varepsilon}_{ijt}$ in (4) or not. Since the residual includes time variation in wages that may stem from the firm side, the worker side, or in match quality, we have opted not to include this variation. However this choice has little impact on the results presented in this paper.

Data

The wage data we use is drawn from the Register Based Labor Market Statistics database (RAMS) maintained by Statistics Sweden. This data base contains information about annual labor earnings for all employment spells in the Swedish private sector from 1985 to 2004. The raw data is compiled by the Swedish Tax Authority in order to calculate taxes. Data include information on annual earnings, as well as the first and last remunerated month. Using this

[1] Including time variation in the market wage, by adding the estimated time dummies to the definition of firm wages (before averaging), would cancel out when calculating the difference (4) since the effects is the same on all wages in the economy.

information, we can construct a measure of monthly wages for each employment spell. The data lacks information on actual hours, so to restrict attention to workers that are reasonably close to full time workers we only consider a person to be a full-time employee if the (monthly) wage exceeds 75 percent of the mean wage of janitors employed by municipalities. We only include employment spells that cover November following the practice of Statistics Sweden. Also, we only count an individual as employed by at most one firm each year by only keeping the employment with the highest wage. Thus, in other words, we focus on individuals primary employment.[2] Moreover, individual characteristics have been added for each employee. These stem from various databases maintained by Statistics Sweden. Specifically, the database contains information on education, both four-digit field and three-digit level codes building on ISCED 97.

The RAMS database also contain a firm identifier, which allows us to match the individual employment spells with information on the employing firm from the Företags Statistiken data base (FS) also maintained by Statistics Sweden. The FS data is on annual frequency and contain information on value added, total labor costs (including e.g. pay-roll taxes) and a five-digit (NACE) sector code for all Swedish limited companies, trading companies and limited partnerships in the private sector from 1996 to 2004 (thus leaving out the smallest firms, i.e. private firms). The number of firms ranges from $265,803$ firms in 1996 to $342,051$ in 1998, all in all, $523,189$ unique companies and $2,810,222$ firm/year observations.

As a first step, we estimate the two-way fixed effects model, outlined in equation (2), on the RAMS data using the methods outlined by Abowd, Creecy, and Kramarz (2002) and relying on a third-order age polynomial. The data we use is the largest linked group in the universe of full-time workers and employers for the years 1985 to 2004 in the Swedish private sector. This group consists of

[2] Using a similar procedure with RAMS data, Nordström Skans, Edin, and Holmlund (2009) found that this gives rise to a computed wage distribution that is close to the direct measure of the wage distribution taken from the 3 percent random sample in the LINDA database, where hourly wage is the measure of pay).

$439,210$ firms, $4,041,023$ individual workers, all in all, amounting to $36,012,606$ worker/firm/year observations, which represents about 99 percent of all observations in the RAMS data.[3] From these results we can compute the (log) difference of the market and the price paid by the firm for a unit of homogenous labor input, i.e. expression (4), for all firms in the linked group. To obtain a measure of labor reallocation, i.e. expression (3), we also need a measure of the firm's weight, $\omega_{jt}s^V_{Ljt}$, i.e. the ratio of the firms total labor cost to the sum of value added in the economy, as well as, the firm's growth rate of labor input, dl_{jt}. The latter measure is derived from the number of employees taken from the RAMS data, counting the number of linked employees per year and firm. To get a measure of the firm's weight, we match our estimates of $\ln(P_L/P_{Lj})$ and the number of employees, both derived from the RAMS data set, to the FS data set using the firm identifier available in both data. Naturally, we cannot match firms that does not employ full time workers in November.[4] All in all, we are able to match $237,738$ firms, constituting about 92 percent per year of the total value added in the FS data. Then, restricting attention to firms where all the needed data are observed in all years of observation, we are left with $763,703$ firm/year observations for $119,105$ firms, constituting about 77 percent of total value added in the FS. Using the combined information from the matched data set we then compute the reallocation measure, R_{Lt}.

Computation

The firm's weight $\omega_{jt}s^V_{Ljt}$ is calculated as the average of the t and $t-1$ observation of the ratio of the firms total labor cost and the sum of nominal value added of the firms in the matched data set. Since we have firms entering and exiting throughout the sample, we face some computational issues to be dealt with. First, we cannot compute ordinary growth rates. Instead, we rely

[3] Here we use the a2group command for determining the largest linked group on which we then estimate the two-way fixed effect model using the a2reg command. Both commands is written for STATA by Amine Ouazad.

[4] Moreover, in a small number of cases we cannot match the data sets due to that Statisitics Sweden only has collected the FS data for a combined group of firms.

on the growth rate used by Davis, Haltiwanger, and Schuh (1997), i.e. $dx_t = (X_t - X_{t-1})/((1/2)(X_t + X_{t-1}))$.[5] Second, for exiting firms we use the lag of (4), the estimated (log) difference of the market and the price paid within the firm for a unit of homogenous labor input, in the exiting year (i.e. for the period after the last observation for the exiting firm). Finally, as shown by Basu and Fernald (2002), the labor reallocation term, R_{Lt}, needs to be multiplied by the value-added markup in order to measure its contribution to TFP growth. For this reason, we multiply our estimate of R_{Lt} with an assumed valued-added markup of 1.15.

Are Wages Allocative?

A key issue for the decomposition above is that we assume that wages are allocative, or in other words, that the firm is on it's labor-demand curve. This is the case if the labor market is perfectly competitive, or less restrictive, if the firm has the right to manage. In both cases, the firm take the wage as a given when making its factor choice (somewhere on its labor demand curve). However, if there is (efficient) bargaining over both labor input and wages between the firm and the union, wages will no longer be allocative. As shown by Dobbelaere and Mairesse (2008), building on work by Crépon, Desplatz and Mairesse (1999, 2005), the first-order conditions from the Nash bargain under efficient bargaining imply that the firm will not equate the marginal revenue of labor to the wage (as under competition in the labor market or under a right-to-manage restriction), but to the reservation wage. Assuming, then that the reservation wage can be captured by the interaction of time and sector dummies, denoted λ_{It}, we would then under the null of efficient bargaining have that $\beta = 0$ in the following regression

$$\ln\left(\frac{P_{jt}Y_{jt}}{L_{jt}}\right) = \alpha_j + \beta \ln w_{jt} + \lambda_{It} + \epsilon_{jt}, \tag{5}$$

where α_j captures the log of the ratio of the markup to the scale elasticity of labor.

[5] Note that the usual growth rate $\Delta x_t = (X_t - X_{t-1})/X_{t-1}$ is related to dx_t as $\Delta x_t = 2dx_t/(2- dx_t)$. Note also that dx_t is bounded by the interval $[-2, 2]$.

Our measure of the left hand side of (5) is computed by dividing our annual measure of value added from the FS database with the number of employees taken from the RAMS data, counting the number of linked employees per year and firm. The wage measure we use is the annual average log (nominal) wage across individuals within each firm. Finally, we include sector dummies (NACE two-digit level) interacted with time dummies in the regression to control for the reservation wage.[6] As can be seen in the first column of table 1, OLS

Table 1: Are Wages Allocative?

	(1) OLS	(2) IV	(3) IV
β	0.799	0.838	0.924
	$(0.007)^{**}$	$(0.030)^{**}$	(0.085)
Lags in Instrument Set:		$\{1,2\}$	$\{2,3\}$
Hansen J (p)		0.169	0.172
Kleibergen-Paap rk LM (p)		0.000	0.000
Observations	754,382	528,334	433,503
Firms	118,175	95,530	87,921

* (**) Denotes significance on the 5 (1) percent level from unity. Standard errors clustered on firms reported inside parenthesis. All specifications include time interacted with two-digit sector-code dummies and firm fixed effects. Hansen J denotes the p-value of the joint test of model specification and instrument validity. Kleibergen-Paap LM denotes the p-value for the null hypothesis of underidentification.

estimation yields a statistically significant estimate of β of 0.799 (s.e. 0.007), thus rejecting the null of efficient bargaining in favor of a right-to-manage view of wage bargaining.[7] Moreover, when using lags of $\ln w_{jt}$ as instruments, to deal with simultaneity and measurement errors, we see that the coefficient raises towards unity. When using the second and third lag as instruments, column (3) in table 1, we arrive at an estimate of 0.924 (s.e. 0.085). Interestingly, this

[6] If the firm switches sectoral code, we assign it to the most commonly observed sectoral code for the firm. We also try to adjust for the (minor) changes in coding in 2003 when the SNI92 sectoral coding system was replaced with the SNI2002 coding system.

[7] Note that the number of observations is slightly lower than the in the sample we perform our baseline decomposition on. This is due to missing information of sector code in some cases and some observations with negative value added.

estimate of β is not statistically different from unity, as expected if wages are allocative and the technology of the firm is Cobb Douglas.

What does the firm effects capture?

From the section above, we know that the firm's average wage relative to the sector is closely related to the firm's marginal revenue of labor relative to the sector. In this section we look into what the firm effects from the wage decomposition (2) captures. Although wages are strongly positively related to differences in the value of the marginal product of labor across firms, the firm fixed effect from the wage decomposition need not to be. This depends e.g. on the correlation between the firm and the individual effects within firms. To look deeper into this issue we first pick out firm fixed effects in the marginal revenue of labor, $\hat{\theta}_j$, from an estimate of

$$\ln\left(\frac{P_{jt}Y_{jt}}{L_{jt}}\right) = \theta_j + \lambda_t + \vartheta_{jt}, \tag{6}$$

including time dummies, λ_t, which will capture the average firm effect, as well as, any time variation in the same (symmetrically relative to the the wage decomposition above). Again, our measure of the left hand side of (6) is computed by dividing our annual measure of value added from the FS database with the number of employees taken from the RAMS data. In a second step, we run the following cross-sectional regression relating the firm fixed effects from the first step to the firm fixed effects from the wage decomposition in (2), $\hat{\gamma}_j$,

$$\hat{\theta}_j = \delta\hat{\gamma}_j + \xi_j. \tag{7}$$

Here we focus on firms with, on average, at least 10 linked employees. This is due to that small firms will have less data points to jointly determine the firm and the individual fixed effects and thus have less precise estimates of the same. The result from this exercise is presented in the first column of table 2.

We arrive at an estimate of δ of 1.129 with a t-ratio of 40.03. Thus, there is a strong positive relationship between the estimated firm fixed effects from the wage decomposition in (2) and the firm fixed effects from our decomposition of

Table 2: What Does Firm Effects Capture?

R.H.S Variable in First Step:	(1) $\ln((P_{jt}Y_{jt})/L_{jt})$	(2) $\ln(P_{jt}Y_{jt}/L_{jt})$	(3) $\ln(Y_{jt}/L_{jt})$
δ	1.129	1.185	1.076
	$(0.028)^{**}$	$(0.089)^{*}$	(0.113)
Observations	23,464	1,503	1,503
Firms	23,464	1,503	1,503

* (**) Denotes significance on the 5 (1) percent level from unity. Sample only include firms with an average of 10 linked employees.

the marginal revenue of labor in (6). The point estimate, which is statistically significantly larger than unity, then suggest a positive correlation between the firm fixed effect and other included components in the wage decomposition within firms.[8]

As a second experiment, we use the fact that for a (small) sub sample of our observations, i.e. single plant firms in the industrial sector, we do have access to a firm-specific producer price index constructed by Statistics Sweden, as well as nominal value added, via the Industry Statistics Data Base (IS). All in all, we are able to match 1,503 firms for the years 1990 – 2002 (with at least 10 linked employees on average) to our original linked employer-employee data set based on RAMS. The firm-specific price index is a chained index with Paasche links that combines plant-specific unit values and detailed disaggregate producer-price indices (either at the goods level, when available, or at the most disaggregate sectoral level available). Note that in the case in which a plant-specific unit-value price is missing (e.g., when the firm introduces a new good), Statistics Sweden uses a price index for similar goods defined at the minimal level of aggregation (starting at 4-digits goods code level). The disaggregate sectoral producer-price indices are only used when a plausible goods-price index is not available (see Carlsson and Nordström Skans, 2011 for further details). Using these price data, we replace the nominal value added with real value added

[8] Although interesting, we defer a deeper analysis of these questions to a different paper.

in the regression (6), thus including a measure of labor productivity instead. In the second column of table 2, we first replicate the first column of table 2 on the subsample (i.e. using nominal value added from the IS data to construct the right hand side variable in the first step) and confirm that we get similar results. The point estimate of δ is slightly larger than in the full sample (1.185 as opposed to 1.129), but the estimate is no longer significantly different from unity due to the larger standard error in the subsample (0.089 as compared to 0.028). When using labor productivity instead of the value of the marginal product in the two step procedure, we also find a strong positive relationship between the firm fixed effects as shown in column (3) of table 2. The point estimate for δ in this case is 1.076 (s.e. of 0.113). Thus we cannot reject the null of a one-to-one relationship between the firm fixed effect from the wage decomposition in (2) and the firm's average productivity relative to the market average.

4 Results

In table 3 we present the results for the labor reallocation term R_{Lt}. In the table we also include the time series for the Swedish market sector TFP growth (since our firm data does not include the public sector), taken from the November 2009 release of the EU KLEMS database (see O'Mahony and Timmer, 2009). Moreover, we also present a cleaned TFP series where we have subtracted the change in the industry capacity utilization rate (collected from Statistics Sweden) times the capital compensation share in (nominal) value added from the original TFP series.[9]

As can be seen in the fourth column of table 3 the contribution from labor reallocation is on average negative in the period 1997-2004, but with positive

[9] The industry capacity utilization rate is measured as production as a share of total production capacity. The capital share is computed as the average of period t and $t-1$ using data on capital compensation and (nominal) value added from the EU KLEMS database. A regression based approach to cleaning the TFP series from variation in utilization yields similar results.

Table 3: Value Added, TFP and Reallocation Growth

	(1)	(2)	(3)	(4)	(5)
Year	VA	TFP	Cleaned TFP	R_{Lt}	R_{Lt}^{Skills}
1995	5.837	0.796	0.475	-	-
1996	2.142	-0.878	-0.412	-	-
1997	4.158	2.319	2.436	0.073	0.046
1998	4.608	0.640	0.016	0.081	-0.036
1999	5.621	0.606	0.788	-0.262	-0.302
2000	5.690	2.325	1.926	-0.184	-0.217
2001	1.238	-1.427	-0.757	0.114	-0.049
2002	2.268	3.092	3.260	-0.121	-0.139
2003	2.461	1.992	1.515	-0.276	-0.240
2004	6.365	4.625	4.069	-0.178	-0.164

Value added and TFP (Market Economy) series is collected from the EU KLEMS Database (See O'Mahony and Timmer, 2009). See main text for description of Cleaned TFP. Numbers correspond to percentage units. Labor Reallocation terms calculated on the unbalanced sample.

contributions in 1997-1998 and 2001. Summing up the changes we see that labor reallocation have lowered the level of GDP with about three quarters of a percentage unit.It is also worth noting that the years 1996 and and 2001 was years with a substantial drop in the growth rate of value added. Thus, from this series it seems as if positive effects from labor reallocation emerge in the wake of recessions. This, in turn, points to theories emphasizing cleansing effects of recessions. Though, the timing of events is not clear from the data. In the 1996 recession it the effect is lagged, whereas in the 2001 event the effect is contemporaneous.

Controlling for Heterogeneity in Skills

As a second exercise we control for skills in the procedure. First, we define LS as individuals with an one-digit ISCED 97 level code smaller than or equal to three (i.e., high-school education or less) and HS as individuals with an one-digit ISCED 97 level code larger than or equal to four (i.e., individuals with tertiary education).[10] Secondly, we estimate the two-way decomposition on two

[10] Individuals with missing information on education are placed in the low skilled group.

separate groups, low skilled (LS) and high skilled (HS) and calculate the the reallocation measure, R_{Lt}^{Skills} as

$$\begin{aligned} R_{Lt}^{Skills} &= \sum\nolimits_{j=1}^{J_t} \omega_{jt} s_{Ljt}^V \sum\nolimits_{s=\{LS,HS\}} \theta_{sjt} \left[1 - e^{\ln(P_{Ls}/P_{Lsj})} \right] dl_{jst}, \\ \ln \widehat{\frac{P_{Ls}}{P_{Lsj}}} &= \frac{1}{\left(\sum_{t=1}^{T} \sum_{j=1}^{J_t} I_{sjt} \right)} \sum\nolimits_{t=1}^{T} \sum\nolimits_{j=1}^{J_t} I_{sjt} \hat{\gamma}_{sj} - \hat{\gamma}_{sj}, \end{aligned} \quad (8)$$

where subindex s index skill groups and θ_{sjt} denotes the (average between periods t and $t-1$ of the) share of skill group s in the total wage bill of firm j, computed from the RAMS data base (see section 3 above for additional computational details). In practice, this procedure implies that we view the high skilled and the low skilled employees of a firm as belonging to two separate divisions with separate wage setting.

Due to that the information content of the education variables improves dramatically with the 1990 census, we focus on the period 1990-2004 when estimating the two two-way decompositions, each specified as in the baseline decomposition outlined above. The largest linked group of low (high) skilled workers/firms consists of $314,502$ $(141,112)$ firms, $2,800,527$ $(829,534)$ individual workers, all in all, amounting to $20,995,544$ $(5,941,282)$ worker/firm/year observations, which represents about 98 (95) percent of all observations for low (high) skilled workers.

Then, restricting attention to firms where all the needed data are observed in all years of observation, we are left with $619,611$ firm/year observations for $99,136$ firms, constituting about 74 percent of total value added in the FS. Using the combined information from the matched data set we then compute the reallocation measure allowing for heterogeneity in skills, R_{Lt}^{Skills}.

In figure 1 we plot R_{Lt}^{Skills} and R_{Lt}. Comparing the series in figure 1, as well as, columns four and five in table 3, it is clear that controlling for skills does not change the cyclical picture of labor reallocation. However, the positive effects in 1998 and 2001 seem to have been driven by skill composition effects in the reallocation flows. Summing up the changes we see that labor reallocation have lowered the level of GDP with about a percentage unit over the period.

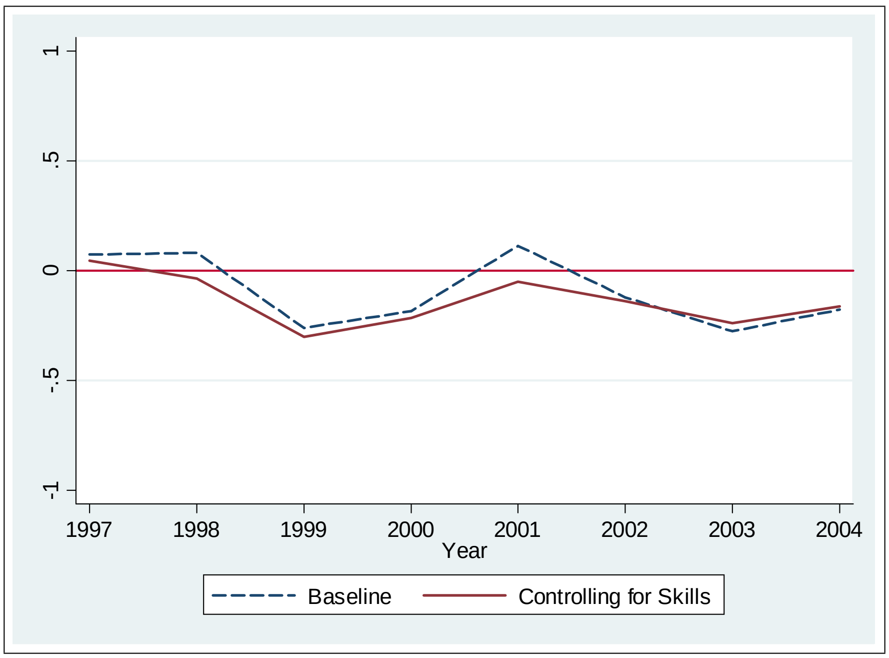

Figure 1: Labor reallocation measures assuming a value-added markup of 15 percent. Labor reallocation series computed on the unbalanced sample with and without controling for heterogeneity in skills.

Entry and Exit

In figure 2, we present the time series for the contribution to TFP growth from labor reallocation computed on the sub-sample of firms that was in continuos operation throughout the sample period, which constitute about 60 percent of total value added in the FS database. For comparison, we also plot the labor reallocation series computed from the unbalanced sample, i.e. also including the effects of entry and exit of firms. Notice that focusing on the sub-sample of

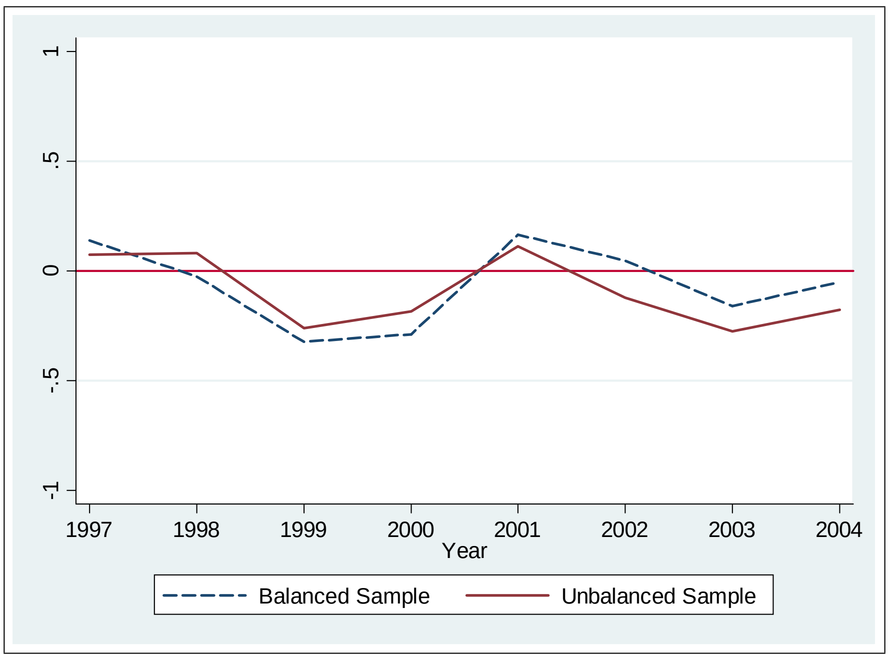

Figure 2: Labor reallocation for both the balanced (excluding effects from entry and exit of firms) and the unbalanced sample assuming a value-added markup of 15 percent.

firms in continuos operation does not change the overall conclusions about the pattern of the labor reallocation term to any substantial degree. However, it is clear from figure 2 that entry and exit of firms have non-trivial effects on the reallocation term. Importantly though, the effects are not symmetrical. After the

1996 decline and following recovery in Value Added growth, entry and exit of firms contributed positively in almost all years, whereas after the 2001 episode entry and exit of firms had negative impact on the labor reallocation term.

Sectoral Contribution

Figure 3 presents a decomposition of the reallocation measure, R_{Lt}, across broad groups of industries. As can be seen in the figure, the main contribu-

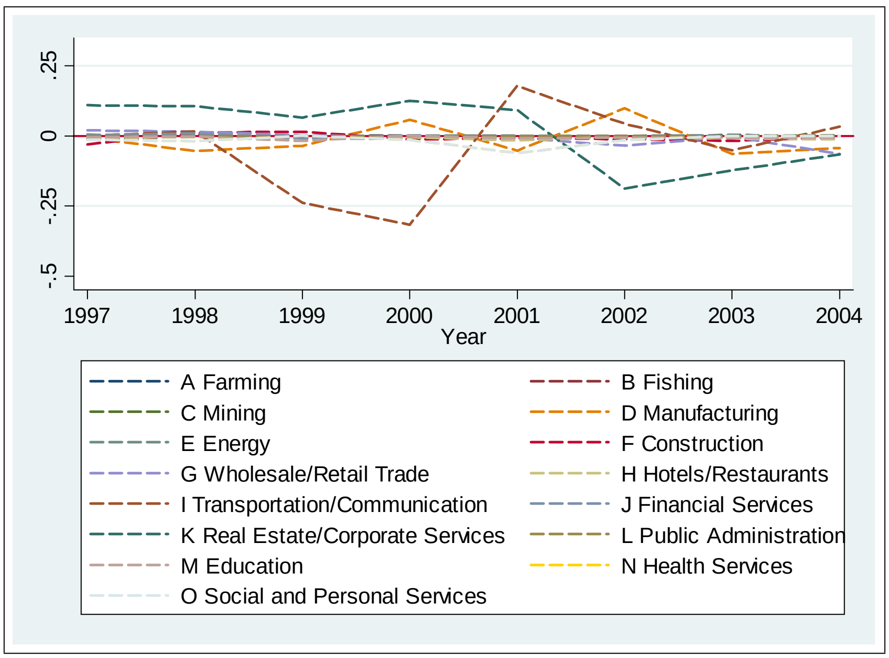

Figure 3: Contribution to total labor reallocation effects across broad industries.

tors to the aggregate reallocation measure, R_{Lt}, is group I (Transportation and Communications), group K (Real Estate and Corporate Services) and to some extent group D (Manufacturing). To gain some additional insights, we have also decomposed the contribution of the two largest contributing groups on the two digit SNI 1992 level in figure 4. As can be seen in the figure, the main contributor to the variation in labor reallocation stemming from group I is industry 64 (Post and Telecommunications) and for group K, the main contributors are

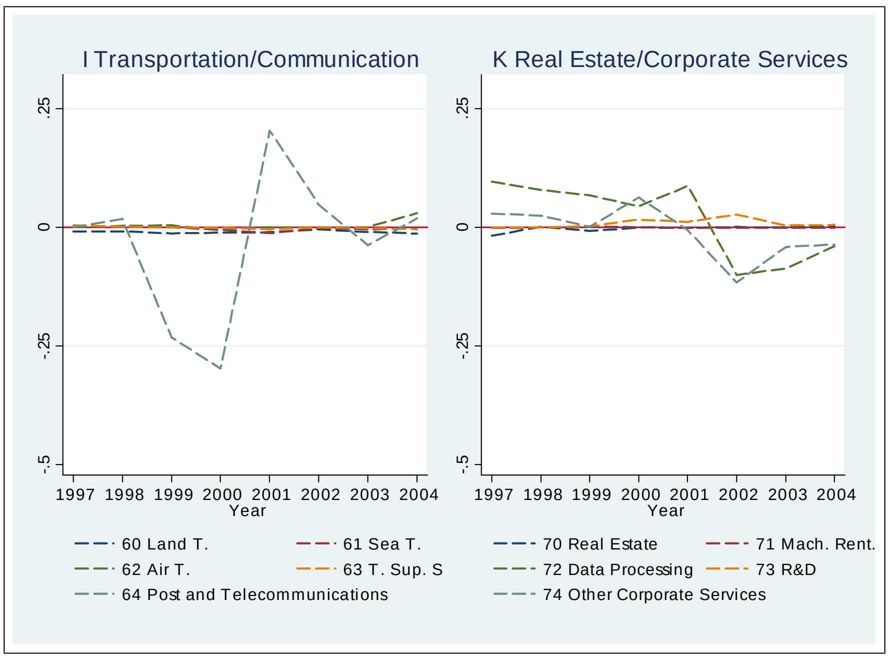

Figure 4: Contribution to total labor reallocation effects across two digit industries in group I and K.

industry 72 (Data Processing) and 74 (Other Corporate Services).[11] In table 4 we present a further look at these sectors. The first three columns correspond to the number of firms in the sector (*Firms*), the number of new firms in the sector (*Births*) and the number of firms exiting from the sector (*Deaths*), respectively.Some caution is warranted here though, since a birth/death also correspond to ownership changes and not only pure firm entry and exit. The last two columns of table present the growth rate of the number of employees, as well as, total real value added in the sector computed from our sample.[12]

Reallocation Flows

Next we try to gain additional insights about the reallocative forces at work in the data. Specifically, we calculate share of new hires from other firms in the private sector coming from a firm with a lower firm effect, i.e. $\hat{\gamma}_j$, each year. Since this measure does not require any information from the FS data we can compute it for the full RAMS sample 1986-2004. This series is plotted in figure 5. From the series we see that, apart from $1986-1987$ and the crisis years of $1990-1992$, the share is slightly below 50 percent. Thus, workers are on average transitioning to similar or worse firms. This is especially apparent in the later part of the sample. Thus, surprisingly, there seem to be no force at work ensuring that workers transition from bad to good firms. Regarding the cyclical pattern, the correlation between the share of new hires coming from worse firms and the growth rate of private sector GDP is -0.414 (p-value 0.078). Thus in bad times the propensity for workers to transition into better firms increases.

[11] Industry 74 includes: Legal, accounting, book-keeping and auditing activities, tax consultancy, market research, public opinion polling, business and management consultancy, holdings, architectural and engineering activities and related technical consultancy, technical testing and analysis, advertising, labour recruitment and provision of personnel, investigation and security activities, industrial cleaning and other business activities (like photographic activities, packaging activities, secretarial and translation activities, call centre activities, design activities, debt collecting and credit rating activities and exhibitions).

[12] To compute real value added in the sector we make use of the sectoral price index for each sector provided by Statistics Sweden. For sector 74 we needed to resort to using a price index for sectors 73/74 due to lack of data.

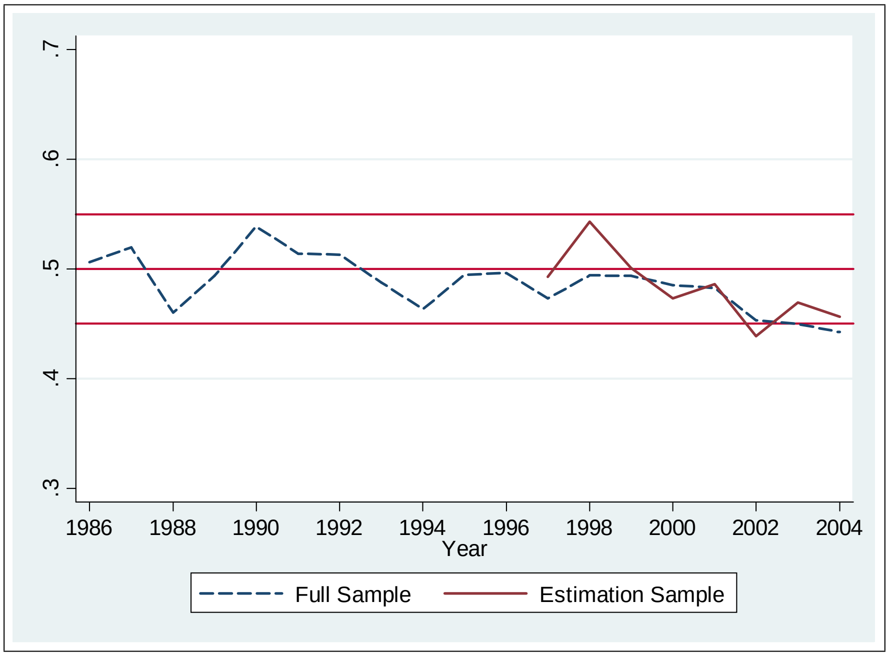

Figure 5: Share of new hires from other firms in the private sector coming from a firm with a lower firm effect.

In figure 5 we also plot the corresponding share from the sample we compute the labor reallocation term on. Although, a bit more volatile, the main picture is similar and the correlation with the full sample is 0.781. Overall, figure 5 seems to provide one explanation for the overall negative contribution of labor reallocation on GDP, that is the lack of any strong mechanism reallocating workers from bad firms to good firms over time.

5 Conclusions

References

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Appendix

A Robustness

In figure 6 we compare the labor reallocation growth term computed with the growth rate used by Davis, Haltiwanger, and Schuh (1997), i.e. $dx_t = (X_t - X_{t-1})/((1/2)(X_t + X_{t-1}))$.with the labor reallocation growth term computed with ordinary growth rates $(lnX_t - lnX_{t-1})$ on the sample of firms in continuous operation throughout the sample period.As can be seen from figure 6, the choice

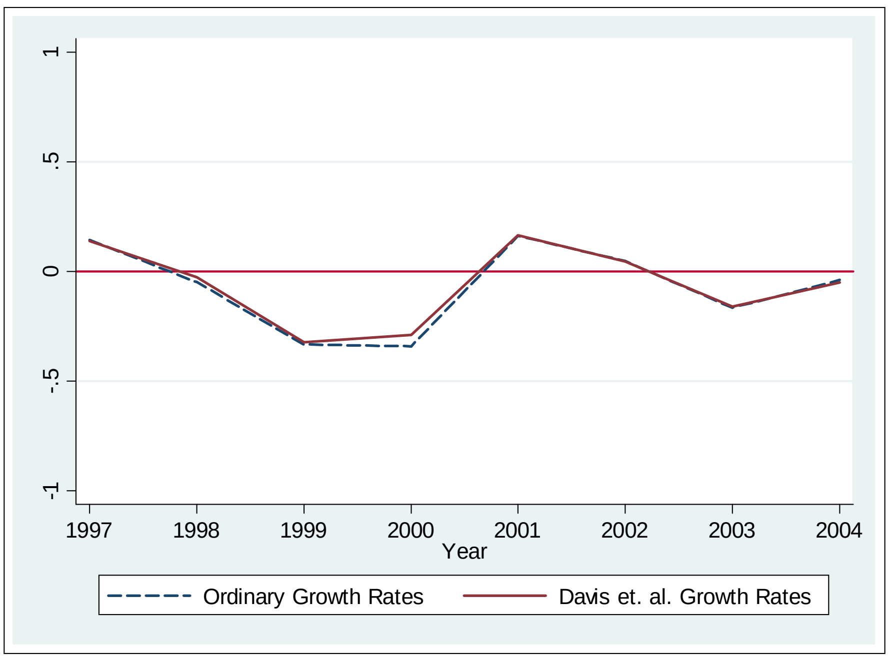

Figure 6: Labor Reallocation Growth computed using ordinary and Davis et. al. (1997) growth rates on the balanced sample.

of growth rates does not have a bearing on the overall results.

Table 4: Sector Details

Industry 64 - Post and Telecommunications						
Year	*Firms*	*Deaths*	*Births*	*N*	*dlnN*	*dlnVA*
1997	84	4	18	57,969	3.765	9.352
1998	85	14	15	24,697	-85.323	12.782
1999	96	5	16	13,562	-59.941	10.048
2000	116	5	25	8,201	-50.302	25.036
2001	133	9	26	14,362	56.032	0.1766
2002	137	14	18	19,603	31.110	-8.020
2003	142	12	17	14,709	-28.722	-14.693
2004	156	4	18	15,982	8.300	10.454
Industry 72 - Data Processing						
Year	*Firms*	*Deaths*	*Births*	*N*	*dlnN*	*dlnVA*
1997	1,800	94	221	31,443	26.767	22.062
1998	2,038	58	296	39,423	22.617	7.544
1999	2,275	55	292	45,721	14.821	13.300
2000	2,684	110	519	48,585	6.076	-9.882
2001	2,944	194	454	57,211	16.343	8.822
2002	3,051	216	323	52,093	-9.372	-9.901
2003	3,211	155	315	47,038	-10.207	-7.809
2004	3,435	128	352	47,574	1.133	15.605
Industry 74 -Other Corporate Services						
Year	*Firms*	*Deaths*	*Births*	*N*	*dlnN*	*dlnVA*
1997	10,416	648	800	96,544	13.294	7.0889
1998	10,942	329	855	105,278	8.661	8.113
1999	11,332	334	724	114,387	8.298	5.334
2000	12,040	402	1,110	121,940	6.394	8.364
2001	12,743	447	1,150	142,072	15.280	7.717
2002	13,338	473	1,068	155,666	9.138	1.164
2003	14,196	400	1,258	157,479	1.158	2.185
2004	15,070	487	1,361	158,567	0.688	0.6199

For growth rates number corresponds to percentage units. The number of firms in period t equals the number of firms in period t-1 plus the net of firm births and deaths in period t.