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ABSTRACT

The Impact of Aggregate and Sectoral Fluctuations on Training Decisions*

So far the literature has found that the effect of macroeconomic fluctuations on training decisions is ambiguous. On the one hand, the opportunity cost to train is lower during downturns, and thus training should be counter-cyclical. On the other hand, a positive shock may be related to the adoption of new technologies and increased returns to skill, making training incidence pro-cyclical. Using the Canadian panel of Workplace and Employee Survey (WES) we find that (i) training moves counter-cyclical with the aggregate business cycle (more training during downturns), while at the same time (ii) the idiosyncratic sectoral shocks have a positive impact on training incidence (more training in sectors doing relatively better). This finding helps us understand training decisions by firms and has important theoretical and policy implications.

JEL Classification: E32, J24

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1 Introduction

The literature has not yet resolved the issue whether investments in human capital are counter-cyclical, pro-cyclical, or a-cyclical. Human capital will increase through training, be that implicit on-the-job training (measured as tenure), or explicit classroom-type training. Our focus in this paper is on the latter: we are interested how the incidence of human capital accumulation through formal training depends on the business cycle.

It is not ex-ante obvious whether the dependence of training on macroeconomic fluctuations should be positive or negative. On the one hand, a negative productivity shock may be associated with increased training, since the opportunity cost to train workers is lower in downturns. On the other hand, a positive shock may be related to the adoption of new technologies which may require training and can provide increased returns to skill.

Both the counter-cyclical and pro-cyclical arguments have sound theoretical justifications, yet we have little evidence which one will hold true or dominate the other empirically. The counter-cyclical channel of lower opportunity cost is highlighted by deJong and Ingram (2001) who find that training activities "are distinctively countercyclical". Arguments for the counter-cyclicality of training can also be found in Devereux (2000) who finds evidence of labour hoarding by firms: during downturns firms will assign high-skill workers to lower-production activities such as training, avoiding some of the fixed costs of firing and re-hiring and ensuring longer tenures for the skilled workers.

While Dellas and Sakellaris (2003) document that college enrollments are counter-cyclical, King and Sweetman (2002) reach the opposite conclusion. Using administrative Canadian data they find that "re-tooling" is pro-cyclical, where re-tooling is measured as quits from work to school. The outside option of higher-skill jobs goes up during episodes of high output, increasing the value of training.

Our contribution is to provide a unifying framework where the two channels coexist. We bring empirical evidence that training is counter-cyclical − as expected, the aggregate output shock has a negative impact on the incidence of firm training. More importantly, we show that the idiosyncratic sectoral shocks are pro-cyclical − firms from sectors which experience a positive shock relative to the rest of the economy have an incentive to train more. This second training channel should be important empirically if for instance sectoral shocks are related to adoption of new technologies. Then, if the idiosyncratic sectoral shocks are more persistent that the aggregate ones, firms are more likely to invest in training following a positive sectoral shock whose benefits last longer. Moreover, the relative positive shock may attract workers from sectors hit by negative shocks, and these workers may require remedial training in specific skills.

To measure the effect of aggregate and sectoral output fluctuations on training incidence we use the panel of the Canadian Workplace and Employee Survey (WES) together with statistics on industrial output. Our major findings are that (i) training moves counter-cyclical with the aggregate output fluctuations (more training in downturns), while at the same time (ii) the relative position of sectoral GDP has a positive impact on training incidence (more training in a sector doing relatively better); finally, (iii) the magnitude of these two channels is comparable. Depending on specification, we find that a percentage point increase in the deviation of aggregate output relative to its trend *decreases* the propensity to train between 1.5 and 2.1 percent, while a percentage point increase in the share of a sector's output *increases* the propensity to train between 0.6 and 1.2 percent. A specification which accounts for heterogeneity in the determinants of training across sectors has the sectoral channel impact even larger, at 3.2 percent, with the aggregate fluctuations channel impact at -2.1 percent. When we consider the impact of output fluctuations on the proportion of workers trained by a firm, the magnitudes are a 1.4 percent reduction in the proportion of workers trained resulting from the aggregate shock, relative to a 1.1 percent increase from the sectoral shock.

We believe that documenting the two channels through which output fluctuations influence the training decision has very relevant theoretical and policy implications. From a theoretical standpoint, we highlight the importance for any models of firm training to incorporate channels stemming from both aggregate and sectoral output fluctuations. Such models will help us get a better understanding of the training decisions by firms. From a policy point of view, we caution that observed declines in training incidence should not necessarily be interpreted as a signal that firms underinvest in training. Instead, lower training by firms could be an optimal response to output fluctuations, be they aggregate or sectoral.

The paper proceeds as follows. Section 2 describes the microdata used in the analysis and references the sources of data for sectoral and aggregate output. Section 3 discusses our main empirical results, as well as sensitivity analysis. Section 4 discusses policy implications and concludes.

2 Data

2.1 WES Data

We use the Canadian Workplace and Employee Survey (WES), which is a nationally representative matched employer-employee survey with a longitudinal design from 1999 to 2005. The sample of locations in the frame is stratified by industry, region and size, and survey weights are used throughout the analysis. We only use the firm side of the WES, as it is difficult to infer firm-specific distributions from the worker side − only very few workers (sometimes as little as two) are interviewed per establishment.

Training is defined as an indicator of classroom (formal) training (CT) offered by firms, who are asked in the survey whether they had offered any training to their workers. We perform sensitivity analysis to two other definitions of training: (i) the percentage of the workforce trained by each firm, and (ii) a training indicator when on-the-job training (OJT) is added to classroom training.[2] Means of the training variables are in the top panel of Table 1. To control for observed firm-specific determinants of training, we follow the literature (*e.g.* Turcotte and Montmarquette (2003)) by using the variables listed in the bottom panel of Table 1.

2.2 Output fluctuation series

To capture the aggregate business cycle effects we use the Gross Domestic Product (GDP) series from Statistics Canada. Series for the overall economy, as well as by sectors, are available since early 1980s and are reported in 2000 constant dollars. Since the time period surveyed by the WES is between April 1^{st} of the previous year and March 31^{st} of the current year we use quarterly GDP aggregated into annual series to correspond to the timing in WES.

[2]Note that on-the-job training may not be a good measure of training in this context. First of all, it is measured with a lot of noise since it comes from the worker side of the survey and thus it is not a representative measure for the firm. Moreover, while on-the-job training can be an important human capital accumulation channel, experience gets accumulated implicitly and it is not necessarily an explicit investment decision by the firm (aside from tenure-related policies). This aggregate measure of training is only of secondary relevance to our analysis.

The classification of sectors in the WES follows for most part the two-digit North American Industry Classification System (NAICS) with a few small differences: in the WES, some industries from the NAICS are aggregated into a single group; and firms from the agricultural sector are not sampled in the WES. Since we use the sectors as defined in the WES, we aggregate the sectors from the output fluctuation statistics in a manner consistent with the WES. The list of sectors used in the analysis together with their relative shares is presented in Table 2. We detrend the real GDP series using the Hodrick-Prescott filter. Figure 1 presents the GDP series and the HP-filtered GDP and trend respectively. In estimation we use either the detrended GDP series (in billions) or, for easier interpretation of the regression coefficients, the ratio of detrended GDP to the HP trend (the latter is unit-of-measure free).

For the relative position of each sector we use the share of that sector's output in total output, using the same series as when constructing the aggregate GDP. For reason of space, we omit from here graphs with the relative sectoral position and training incidence by respective sectors.

3 Evidence on macroeconomic fluctuations and training

3.1 Model specification

In our main specification we use a binary response model to measure the impact of business cycles on the propensity of a workplace to offer training. Let D_{it} be a binary training indicator taking the value 1 if firm i from sector j provided training in period t, and 0 otherwise. We estimate the probability of firm i to train its workers in period t, P_{it}, conditional on the information set Ω_{ijt}: $P_{it} = Pr(D_{it} = 1|\omega_{ijt}) = E[D_{it}|\omega_{ijt}]$, where ω_{ijt} is a collection of firm-specific characteristics X_{it} (as mentioned in Table 1) and sector- or economy-wide characteristics Z_{jt}. The conditional expectation is modeled using the following specification: $E[D_{it}|\omega_{ijt}] = \Lambda(\omega\gamma) = \Lambda(\alpha_i + \beta X_{it} + \delta Z_{jt} + u_{it})$ where Λ is the probability link function, logistic in our implementation, and γ the set of coefficients.

The results come from conditional fixed effects logistic regressions[3] using panel weights provided by WES and clustering by sectors. The Hausman test rejected firm-specific random

[3]Except for when the left-hand side variable is continuous (fraction of workforce trained) when we implement panel OLS and tobit to account for the mass of firms with zero training.

effects in favour of the fixed effects specification.

The economy-wide factors are the deviations of GDP from the HP trend (in billions) and the share of each sector in total output. All results reported here also include the HP-filtered trend as a regressor. Sensitivity analysis (available form the authors) indicates that including or not the trend does not change the other coefficients much, and does not change the story at all. We report estimation coefficients in all results. For the logit case, to obtain marginal effects the coefficients have to be scaled by a factor of $\Lambda' = \Lambda(\omega\gamma)(1 - \Lambda(\omega\gamma)$ with the logistic *cdf* $\Lambda(x) = \frac{e^x}{1+e^x}$. The factor of proportionality $\Lambda(1-\Lambda)$, computed as average over all observations, is around .25 in all specifications. We report the factor of proportionality in the footnotes of each respective results table. To make the results easier to interpret, we report coefficients for the aggregate fluctuation measured as ratio of detrended GDP to the HP trend, since it is unit-of-measure free. In the footnotes of each table we also report the coefficients for the real detrended GDP measured in billion Canadian dollars (base 2000).

3.2 The impact of output fluctuations on training incidence

We start by presenting the main results in Table 3. The coefficient on aggregate output fluctuations is negative and significant, implying that training is counter-cyclical. In other words, firms are more likely to provide their workers with training during downturns. This is in line with the argument that workers are relatively less productive during downturns, hence the opportunity cost of training (foregone output) is relatively smaller during recessions. The magnitude of the coefficient implies that a percentage point change in the ratio of GDP fluctuations to the HP trend will decrease the probability that a firm trains by 1.5 percent.[4]

The coefficient on the relative sectoral output variable is positive. This tells us that firms are also more likely to train if the sectors they operate in are hit by relatively more favorable shocks. This second channel is related to the fact that sectors doing relatively better will attract workers from sectors doing relatively worse, and these workers will need remedial skill training in the new sector. The other explanation, that firms in sectors who do relatively better (even in a downturn) may adopt new technologies which require a better trained workforce, while still present, is also captured to some extent by other firm-specific controls such as "innovation".

[4] The marginal effect is the coefficient -0.061 times the logistic factor of proportionality .244.

The marginal effect of the relative sectoral channel is slightly smaller than the one of the aggregate fluctuations, but of a comparable order of magnitude: a percentage point increase in the relative sector position will decrease the probability that a firm trains by 1.2 percent.[5]

For the remainder of this section we present some evidence that our quantification of the two output fluctuation channels determining training incidence is robust to different specifications and definitions of training.

3.3 Sensitivity Analysis

3.3.1 Firm-specific determinants of training incidence

In terms of the firm-specific factors that influence training, we find from Table 3 that on average high training firms are characterized on the average as being more innovative, more diversified and larger, more likely to be not unionized, and less likely to employ sales and technical personnel. This is in line with what has been documented elsewhere in the literature of firm training determinants – see for instance Lynch and Black (1998) for the U.S., Dearden, Reed, and Reenen (2006) for the U.K., and Turcotte and Montmarquette (2003) for Canada.

Note that in all specifications we control for a firm-reported measure of innovation and adoption of new technologies. Moreover, Table 4 reports the correlations between the skill distribution of the workforce and the idiosyncratic sectoral shock. There is a negative correlation between the sectoral shock and the fraction of unskilled "production" workers, while all other correlations are positive. We interpret this as suggestive evidence that the idiosyncratic sectoral shock channel induces reallocation of lower-skill workers from the sectors doing relatively poorly to the sectors doing relatively better.

A specification accounting for heterogeneity in the determinants of training has found that these variables can have different impacts depending on the sector they apply to. The detailed coefficients form the analysis with heterogeneous determinants of training by sectors can be found in Appendix Appendix A. The differences are statistically significant, indicating the need for caution when considering models of firm training. For instance, firms in manufacturing have the opposite training determinants in terms of the skill of their workforce (measured as percentage from different skill categories). This is a relevant finding given that a lot of studies

[5]The marginal effect is the coefficient 0.026 times the logistic factor of proportionality .244.

focus exclusively on the manufacturing sector. At least for the Canadian context, results for manufacturing firms only can give opposite conclusions from the average.

A notable finding from the heterogeneity analysis is that the sectoral fluctuations channel shows a larger magnitude − compared to the other specifications, and compared to the aggregate fluctuations channel (.134 logit coefficient, which translates into a sizeable .0348 marginal effect).

3.3.2 Marginal benefits of past training and training incidence

In their training decisions, firms may take into account productivity improvements coming from previous episodes of training. If a firm had experienced positive training impacts, it may be more likely to engage in training again. Kayahan (2007) documents a correlation between past returns to training for the firm and training incidence. We extend these findings here by exploiting the variation across sectors and time to explicitly formalize a relationship between past benefits of training for the firm and current training incidence.[6]

In Table 5 we present sensitivity results for the specification where the marginal benefit of past training is included as a determinant of training. Our story and our results do not change when adding lagged marginal benefits of training. If anything, the effect of output fluctuations on training propensity are larger, -2.1 percent for the aggregate fluctuations relative to trend, and 1.2 percent for the relative sectoral position, while the gap between the two channels (in absolute value) has shrunk. As for the impact of previous marginal benefits of training, they are positive and significant.[7]

[6]Measuring the returns to training for the firm is a non-trivial task. Most of the literature has focused on estimating returns to training on the worker side, and because of lack of appropriate firm-level data not much work has been done on estimating the impact of training on productivity. We are only aware of three studies which have investigated the impact of training on firm productivity by estimating a firm-level production function: Dearden, Reed, and Reenen (2006) for the U.K., Almeida and Carneiro (2005) for Portugal, and Kayahan (2007) for Canada. All these papers exploit the longitudinal nature of firm-level data (Almeida and Carneiro (2005) and Kayahan (2007)) or aggregate industry data (Dearden, Reed, and Reenen (2006)) to estimate production functions that exploit heterogeneity at the firm or industry level, accounting for training as an input in the accumulation of human capital. The econometric methodology, GMM Instrumental Variable estimator using lagged first differences of variables as instruments in the level equations (Blundell and Bond (1998)), addresses both the issue of training endogeneity and unobserved firm characteristics.

[7]In other specifications, such as the one in Table 6, the benefits from the first pre-training lag can be insignificant but negative, while the second lag benefits are always significant and positive. This can be attributed to some persistent effect of training, which could make it unnecessary for firms to train every single period.

3.3.3 Definition of training: percentage of workforce trained

For this sensitivity check we change the dependent variable from a dychotomous indicator of training propensity to a continuous indicator where the left-hand side variable is the percentage of workforce trained. These results are in Table 6, and indicate the same story as the one from the propensity to train model.A percentage point increase in the deviation of (detrended) output from HP trend decreases the percentage of workforce trained by 1.4 percent, while a percentage point increase in the share of a sector in total output increases the percentage of workforce trained by 1.1 percent.

3.3.4 Definition of training: adding on-the-job training to classroom training

Here we conduct the same analysis as we have done in the previous section, only this time the dependent variable is a binary variable indicating whether the firm has provided any training at all: on-the-job implicit training is added to formal classroom training. While we have our reservations about this measure (it comes from the matched worker side of the survey, where only a handful of workers are interviewed for each firm), this is a more general measure of training which includes both types of training (formal and/or informal). We have other reservations as well, because conceptually on-the-job training measures a very different type of human capital acquisition than classroom training. The results from this analysis are presented in Table 7. While the signs of the relevant coefficients are the same as before, in this analysis the aggregate output shock effect is no longer significant (while the sectoral effect is). We believe this has a lot to do with the noise in constructing this training measure.

4 Conclusion

The sectoral analysis is very important in specifying the links between the aggregate business cycle, sectoral idiosyncratic shocks, firm innovation, and the incidence and intensity of training. We find training to be counter-cyclical − firms train more in downturns, while sectoral shocks have a positive impact on training incidence − more training when the sector has a relatively better position. The magnitudes of these adjustments are of similar order, with the relative sectoral channel having either a slightly smaller impact or a slightly larger impact than the aggregate fluctuations one, depending on specification.

We believe the finding of two opposing channels through which output fluctuations affect training decisions has large relevance for at least three reasons: (i) first, it gives us better insight in understanding firms' training decisions over the business cycle (ii) second, it gives us a glimpse into how the persistence of aggregate relative to sectoral shocks plays into the human capital accumulation channel, and (iii) finally, it helps policy-makers understand that fluctuations in training incidence may be optimal responses to macroeconomic shocks, and not necessarily indicators of underinvestment in training.

In terms of a model, a simple illustration makes our point. Consider the basic Mortensen-Pissarides search and matching model, where the productive match is subject to a productivity shock $y = p\epsilon$, with p the aggregate shock and ϵ the idiosyncratic sectoral one. Let α be a match-specific productivity. Training is available for meetings above some productivity threshold, below which no matches are formed, with our without training. In equilibrium only matches above the productivity threshold but below some cut-off realized productivity are trained. Firms train as long as the benefit from training is higher than the cost. When an aggregate negative shock p hits all sectors, training will increase as long as the marginal cost of training is higher than the marginal benefit with respect to p, which is easy to achieve under very reasonable parametrizations. When an idiosyncratic shock ϵ hits sectors there will be worker reallocation from the low to the high productivity sectors. This decreases the average match quality α in the sectors not hit by negative shocks and increases worker congestion, to the extent that more matches will fall within the training productivity interval; thus, more training will take place in the relatively better sectors. A sketch of this model is presented in Appendix B.

In terms of policy, there is scope for government intervention in training as long as policy-makers worry that firms under-invest in training. In deciding how much training to provide, firms will take into consideration how likely the workers are to stay with the firm once the training is completed. If private returns to training are large but firms do not train for fear of losing workers to higher-paying jobs, then it is socially optimal to provide government training, or to provide workers/firms with incentives to increase training.[8] Documented aggregate and

[8] As for the effectiveness of firm versus government training, contrary to what has been the status-quo in the literature, recent work by Kambourov, Manovskii, and Plesca (2009) has shown that the impact of government training programs is more positive than previously thought. Once post-training occupation mobility behaviour is accounted for, wage returns from government-sponsored training are comparable to those from employer-sponsored training, making the case for a possible role for government intervention in training.

sectoral output fluctuations can inform policy whether observed trends in training are healthy, as dictated by economic circumstances, or whether firms under-invest in training and therefore direct government intervention should be recommended.

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Figure 1: GDP, HP-filtered GDP, and HP trend

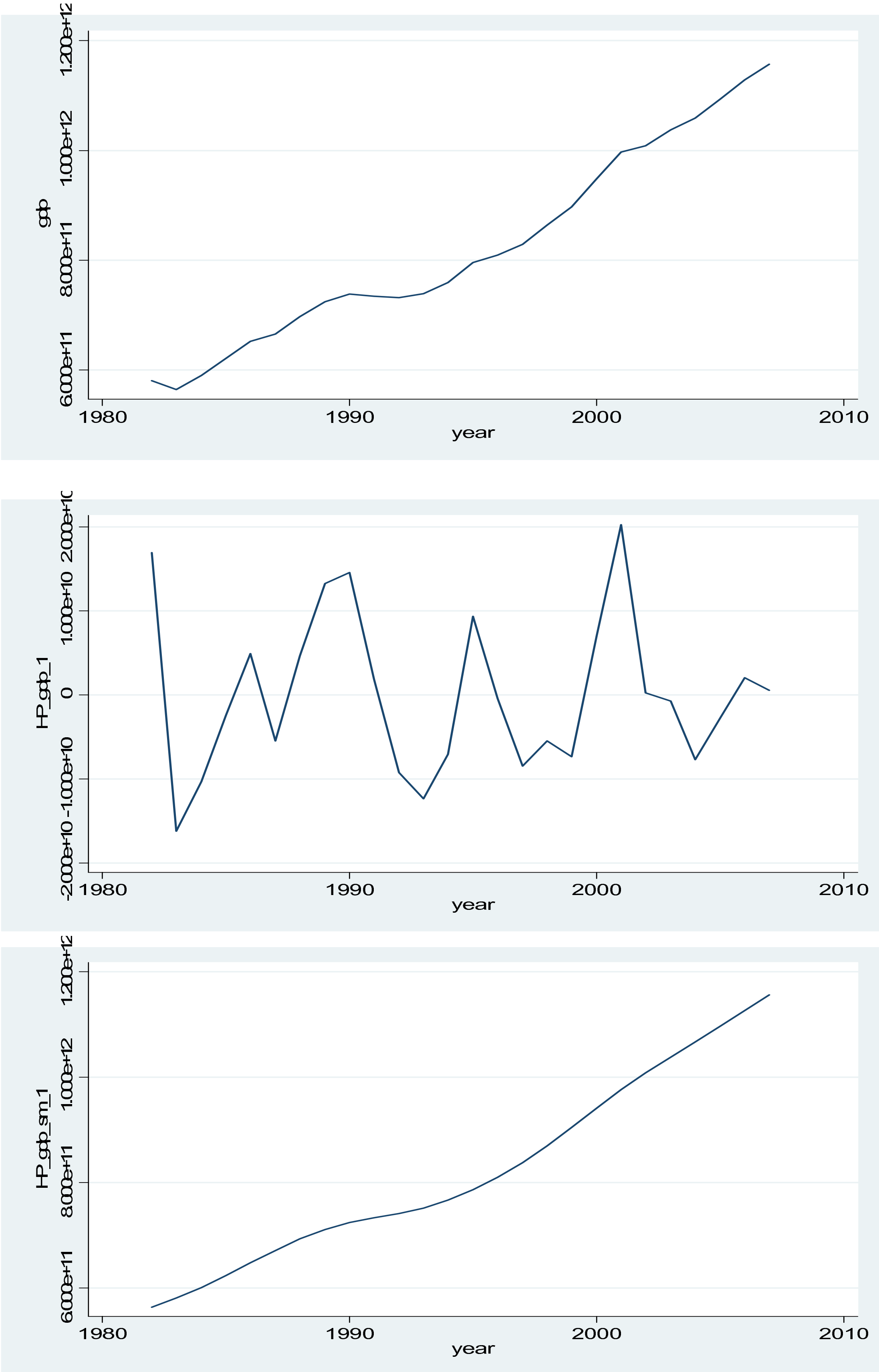

Table 1: Statistics for Training and for Firm Specific Variables

	Variable Description	Mean	Std Dev
Classroom Training Indicator		0.340	0.474
% Workforce Trained		0.213	0.446
Classroom Training plus OJT Indicator		0.577	0.494
Firm size	Number of workers employed by the workplace	16.7	49.7
Innovation	Adoption of innovation and/or new technology by the workplace	0.489	0.499
Unionized	Indicator whether the workplace is unionized	0.057	0.232
Multiple loc.	Indicator whether the workplace belongs to a multiple-location firm	0.455	0.498
Market	The most dominant sales market of the firm		
	Local	0.855	0.351
	Canada	0.095	0.292
	World	0.049	0.217
Skill	% of workforce in skill groups		
	Administrative	0.197	0.283
	Managers	0.202	0.231
	Others	0.074	0.225
	Professionals	0.059	0.169
	Sales	0.122	0.249
	Technicians	0.148	0.263
	Production	0.198	0.312

Table 2: Sectors in the Analysis

Sector	Relative Size (%)
Forestry and Mining	5 %
Construction	13 %
Transportation, Warehouse, Wholesale Trade	13 %
Information, Communication and Utilities	10 %
Finance and Insurance	7 %
Real Estate	6 %
Business Services	10 %
Education and Health	4 %
Manufacturing	21 %
Retail Trade and Consumer Services	11 %
Number of firms	5535

Table 3: The Impact of Aggregate and Sectoral Output Fluctuations on Training Incidence

Variables	Coefficients[a]	Std. Err
GDP fluctuations [b]	-0.061	0.0023
Sector to GDP ratio	0.026	0.002
Innovation	0.604	0.005
Market: Canada [c]	0.080	0.010
Market: World	0.457	0.019
ln (Firm size)	0.536	0.008
Multiple locations	0.094	0.006
Unionized	-0.118	0.017
% Administrative [d]	0.552	0.020
% Managerial	0.535	0.020
% Other	1.127	0.020
% Sales	0.268	0.020
% Production	0.630	0.019
% Technical	0.112	0.018
GDP trend	0.001	0.00004

[a] Factor of proportionality for marginal effects $\Lambda(1-\Lambda) = .244$

[b] Coefficient for detrended GDP relative to HP trend. For the GDP expressed in real billions the coefficient is -0.007 (0.0002).

[c] Base category: Local market

[d] Base category: Professional

Table 4: Correlations Between Sectoral Relative Position and Workforce Skill Distribution

% Workforce	Sector to GDP ratio
Administrative	-0.1267
Sales	-0.0736
Managerial	-0.0274
Professional	-0.0975
Technical	-0.0682
Production	0.2838
Other	-0.0684

Correlations significant at 1% level.

Table 5: The Impact of Aggregate and Sectoral Output Fluctuations on Training Incidence: Controlling for Previous Training Benefits

Variables	Coefficients	Std. Err
GDP fluctuations	-0.085	0.005
Sector to GDP ratio	0.050	0.004
Innovation	0.721	0.008
Market: Canada [a]	0.361	0.014
Market: World	0.502	0.028
ln (Firm size)	0.602	0.013
Multiple locations	-0.100	0.025
Unionized	1.669	0.034
% Administrative [b]	1.395	0.030
% Managerial	1.616	0.032
% Other	0.820	0.030
% Sales	1.521	0.028
% Production	0.914	0.025
% Technical	0.002	0.0001
GDP trend	0.002	0.0001
MB_{t-1}	0.104	0.029
MB_{t-2}	0.277	0.026

[a] Factor of proportionality for marginal effects $\Lambda(1-\Lambda) = .246$

[b] Coefficient for detrended GDP relative to HP trend. For the GDP expressed in real billions the coefficient is -0.009 (0.001).

[c] Base category: Local market

[d] Base category: Professional

Table 6: The Impact of Aggregate and Sectoral Output Fluctuations on Training Intensity: % Workforce Trained)

Variables	Coefficients [a]	Std. Err
GDP fluctuations [b]	-0.014	0.007
Sector to GDP ratio	0.011	0.006
Innovation	0.074	0.011
Market: Canada [c]	0.027	0.023
Market: World	0.068	0.042
ln (Firm size)	-0.044	0.020
Unionized	-0.078	0.039
% Administrative [d]	0.121	0.048
% Managerial	0.117	0.045
% Other	0.193	0.048
% Sales	0.092	0.045
% Production	0.186	0.044
% Technical	0.082	0.042
GDP trend	0.00003	0.0002
MB_{t-1}	-0.021	0.034
MB_{t-2}	0.011	0.034

[a] Coefficients are marginal effects

[b] Coefficient for detrended GDP relative to HP trend. For the GDP expressed in real billions the coefficient is -0.001 (0.001).

[c] Base category: Local market

[d] Base category: Professional

Table 7: The Impact of Aggregate and Sectoral Output Fluctuations on Training Incidence: Adding OJT to CT in the Definition of Training

Variables	Coefficients [a]	Std. Err
GDP fluctuations [b]	0.003	0.002
Sector to GDP ratio	0.060	0.002
Innovation	0.492	0.005
Market: Canada [c]	0.327	0.010
Market: World	-0.358	0.016
ln (Firm size)	0.351	0.008
Multiple locations	-0.084	0.006
Unionized	-0.307	0.016
% Administrative [d]	0.210	0.018
% Managerial	0.049	0.018
% Other	-0.038	0.018
% Sales	0.463	0.018
% Production	0.338	0.017
% Technical	-0.050	0.017
GDP trend	0.00009	0.00004

[a] Factor of proportionality for marginal effects $\Lambda(1-\Lambda) = .246$

[b] Coefficient for detrended GDP relative to HP trend. For the GDP in real billions the coefficient is 0.000 (0.0002).

[c] Base category: Local market

[d] Base category: Professional

Appendix A Heterogeneity in training determinants

Table A1: Sectoral Heterogeneity in Firm-Specific Determinants of Training

Variable	Coef.	Std.Er.	Variable	Coef.	Std.Er
GDP fluctuations	-0.090	0.002			
Sector to GDP ratio	0.134	0.006			
Innovation	0.218	0.018	Administrative	-0.855	0.092
Innovation* Sector 1	-0.252	0.044	Administrative* Sector 1	-0.250	0.179
Innovation* Sector 2	0.407	0.025	Administrative* Sector 2	2.141	0.128
Innovation* Sector 3	-0.066	0.023	Administrative* Sector 3	1.316	0.103
Innovation* Sector 4	0.524	0.039	Administrative* Sector 4	1.604	0.141
Innovation* Sector 5	0.673	0.026	Administrative* Sector 5	0.330	0.107
Innovation* Sector 6	-0.496	0.049	Administrative* Sector 6	3.487	0.167
Innovation* Sector 7	0.972	0.023	Administrative* Sector 7	1.055	0.099
Innovation* Sector 8	0.293	0.024	Administrative* Sector 8	1.607	0.099
Innovation* Sector 10	0.431	0.021	Administrative* Sector 10	3.388	0.110
Market Canada	0.248	0.025	Sales	-3.492	0.113
Market Canada* Sector 1	-1.677	0.071	Sales* Sector 1	1.570	0.306
Market Canada* Sector 2	-0.279	0.044	Sales* Sector 2	8.691	0.171
Market Canada* Sector 3	-1.193	0.032	Sales* Sector 3	5.166	0.118
Market Canada* Sector 4	0.057	0.071	Sales* Sector 4	3.921	0.173
Market Canada* Sector 5	0.689	0.047	Sales* Sector 5	2.363	0.124
Market Canada* Sector 6	-0.375	0.069	Sales* Sector 6	7.040	0.207
Market Canada* Sector 7	0.755	0.041	Sales* Sector 7	4.179	0.122
Market Canada* Sector 8	1.343	0.061	Sales* Sector 8	14.370	0.495
Market Canada* Sector 10	-0.016	0.041	Sales* Sector 10	4.238	0.123
Market World	0.057	0.034	Managerial	-2.093	0.095
Market World* Sector 1	0.227	0.106	Managerial* Sector 1	4.637	0.161
Market World* Sector 2	-12.084	660.719	Managerial* Sector 2	5.071	0.115
Market World* Sector 3	-0.870	0.063	Managerial* Sector 3	2.734	0.104
Market World* Sector 4	-0.127	0.074	Managerial* Sector 4	1.809	0.135
Market World* Sector 5	1.620	0.102	Managerial* Sector 5	1.324	0.109
Market World* Sector 6	1.061	0.260	Managerial* Sector 6	7.045	0.197
Market World* Sector 7	1.899	0.054	Managerial* Sector 7	2.802	0.103
Market World* Sector 10	0.046	0.130	Managerial* Sector 8	4.202	0.109
ln (Firm size)	1.189	0.020	Managerial* Sector 10	1.554	0.107
ln (Firm size)* Sector 1	0.096	0.043	Technical	-1.981	0.076
ln (Firm size)* Sector 2	-0.347	0.027	Technical* Sector 1	3.886	0.133
ln (Firm size)* Sector 3	-0.561	0.023	Technical* Sector 2	4.268	0.095
ln (Firm size)* Sector 4	-0.561	0.034	Technical* Sector 3	1.993	0.087
ln (Firm size)* Sector 5	-1.105	0.033	Technical* Sector 4	0.994	0.134
ln (Firm size)* Sector 6	-1.782	0.048	Technical* Sector 5	1.964	0.095
ln (Firm size)* Sector 7	-0.741	0.024	Technical* Sector 6	7.975	0.269
ln (Firm size)* Sector 8	-0.972	0.030	Technical* Sector 7	2.960	0.085
ln (Firm size)* Sector 10	-0.733	0.025	Technical* Sector 8	2.425	0.083
Multiple locations	0.060	0.018	Technical* Sector 10	0.088	0.095
Multiple locations* Sector 1	-1.503	0.049	Production	-1.794	0.075
Multiple locations* Sector 2	0.017	0.029	Production* Sector 1	2.748	0.137
Multiple locations* Sector 3	0.288	0.023	Production* Sector 2	4.589	0.101
Multiple locations* Sector 4	0.715	0.036	Production* Sector 3	1.885	0.084
Multiple locations* Sector 5	0.666	0.026	Production* Sector 4	0.211	0.138
Multiple locations* Sector 6	0.270	0.050	Production* Sector 5	1.727	0.098
Multiple locations* Sector 7	-0.188	0.023	Production* Sector 6	5.929	0.183
Multiple locations* Sector 8	-0.270	0.023	Production* Sector 7	-2.272	0.100
Multiple locations* Sector 10	-0.196	0.021	Production* Sector 8	3.625	0.095
Unionized	0.588	0.053	Production* Sector 10	4.684	0.092
Unionized* Sector 1	-0.777	0.121	Other	-1.181	0.099
Unionized* Sector 2	-1.529	0.068	Other* Sector 1	3.098	0.188
Unionized* Sector 3	-0.679	0.071	Other* Sector 2	3.602	0.133
Unionized* Sector 4	-0.339	0.084	Other* Sector 3	2.735	0.109
Unionized* Sector 5	0.685	0.074	Other* Sector 4	0.533	0.155
Unionized* Sector 6	-3.684	0.227	Other* Sector 5	-0.650	0.122
Unionized* Sector 7	-0.297	0.074	Other* Sector 6	4.957	0.191
Unionized* Sector 8	-0.688	0.181	Other* Sector 7	0.458	0.113
Unionized* Sector 10	-2.097	0.071	Other* Sector 8	3.110	0.112
GDP trend	0.001	0.000	Other* Sector 10	4.269	0.112

Appendix B Sketch of Mortensen-Pissarides model with training

The model presented here is a very stylized textbook model of training and productivity based on Pissarides (2000), which serves to illustrate the relationship between aggregate and sectoral specific shocks and training by firms.

Firms open vacancies whenever they want to fill a job. Keeping a vacancy open implies a cost c. The rate at which unemployed workers and open vacancies meet, in each sector is regulated by meeting functions $m(v_i, u)$ that depends on the number of unemployed workers and vacancies created in the particular sector i. Once there is a meeting firms observe the worker specific productivity α and decide if the candidate is suitable for the job. A productive match is formed if α is above the reservation value R_i. Upon creating a match the firm evaluates the opportunity to train the worker. Depending on the productivity of the worker and whether the worker has been trained or not a wage $w^k(\alpha)$ is paid, with $k = u, \tau$ for untrained and trained respectively. Training, as well as the productivity α, are specific to the match: if the match is dissolved the worker returns to the pool of unemployed workers with unknown productivity, and with the same expected productivity she had before the match (and same as everybody else in that pool). After a match is created shocks can arrive at a rate λ which will dissolve the match and let the worker be unemployed again. Wages are set by Nash bargaining.

Following Pissarides (2000) the meeting function is written as $m(v_i, u) = m(1, \frac{u}{v_i})v_i \equiv q(\theta_i)v_i$, where $\theta_i = \frac{v_i}{u}$ is market tightness in sector i. Given the meeting function the ratio at which vacancies are filled can be defined as $q_i^f = q(\theta_i) \int_{R_i}^b dF(\alpha)$, where b is the upper limit of the shock distribution and r is the reservation value. The ratio at which unemployed workers find a job is respectively given by: $q_i^w = q(\theta_i)\theta_i \int_{R_i}^b dF(\alpha)$.

Appendix B.1 Value of a match to an employer

The value of a job to an employer depends on the productivity specific to that match and the level of training given to the worker. We assume that the level of training is decided at the starting of a match (empirical evidence from the NLSY suggests that training takes place very early in the employer tenure), and that the cost of training is paid by the employer every period the worker is employed (such an insurance-type cost scheme enables firm training even if training is in transferable general skills). Output is the product of the shock α and the productivity parameter $y_i = p\epsilon_i$, where p is an aggregate productivity shock and ϵ_i a sector-specific idiosyncratic one.

The value of a match to an employer who trains $J_i^u(\alpha)$ − or not $J_i^u(\alpha)$ − is given by:

$$rJ_i^u(\alpha) = y_i\alpha - w_i^u(\alpha) - \lambda J_i^u(\alpha). \tag{1}$$

$$rJ_i^\tau(\alpha) = y_i h(\alpha) - w_i^\tau(\alpha) - C(y\alpha) - \lambda J_i^\tau(\alpha). \tag{2}$$

Here $h(\alpha)$ is a function that describes how productivity increases with training and it is assumed to be increasing in α, $C(y\alpha)$ is the cost of training, and w^τ and w^u the wage rates offered to the trained and respectively untrained workers.[9]

The asset equations above describe the value of a match. Training is required for workers with productivity levels above the reservation threshold R_i but below $\alpha_{\tau,i}$, while is not required for workers with higher productivity. Given a unique training reservation productivity, the asset equations can be combined in one match value as follows:

$$J_i^e = \int_{R_i}^{\alpha_{\tau,i}} J_i^u dF(v) + \int_{\alpha_{\tau,i}}^{b} J_i^\tau(v)dF(v). \tag{3}$$

where the superscript e indicates the expectation conditional on α being greater than the productivity threshold R_i.

Appendix B.2 Value of a match to a worker

The value of a match to a worker is determined by the following asset equations:

$$rW_i^u(\alpha) = w_i^u(\alpha) + \lambda[U - W_i^u(\alpha)], \tag{4}$$

$$rW_i^\tau(\alpha) = w_i^\tau(\alpha) + \lambda[U - W_i^\tau(\alpha)]. \tag{5}$$

Similarly to the previous case for the employer we can write,

$$W_i^e = \int_{R_i}^{\alpha_{\tau,i}} W_i^\tau(v)dF(v) + \int_{\alpha_{\tau,i}}^{b} W_i^u(v)dF(v). \tag{6}$$

[9] Note that if we were interested in say the optimal amount of training T offered, we could introduce it via the benefit and cost of training $h(\alpha, T)$ and $C(T, y\alpha)$ where T can denote the amount of training, $h(\alpha, T)$ is concave in T and $C(T, y\alpha)$ is convex in T. Here we focus on training incidence instead.

Appendix B.3 Value of a vacancy and of unemployment

The value of setting a vacancy to an employer is

$$rV_i = -c + q_i^f [J^e - V].$$

In equilibrium free entry sets the value of a vacancy to zero.

The value of unemployment to a worker depends on the number and the conditions of all sectors in the economy, since each unemployed worker can be matched stochastically with any of the firms opening vacancies in each sector. For simplicity, we assume that there are only two sectors in the economy indexed by $i = 1, 2$. In this case we have that the total number of vacancies formed in the economy is given by $v = v_1 + v_2$ and the overall tightness of the economy is described by $\theta = \theta_1 + \theta_2$. The value of unemployment is then

$$rU = z + q_1^w [W_1^e - U] + q_2^w [W_2^e - U],$$

where z represents unemployment contingent income.

Appendix B.4 Wages and Training

Assuming that the wage rates are set following the Nash bargaining rule, after some algebra we can derive the wage rate for trained and untrained workers,

$$w_i^\tau(\alpha) = \beta[y_i h(\alpha) - C(y_i \alpha)] + (1-\beta)z + \beta c\theta \tag{7}$$

$$w_i^u(\alpha) = \beta y_i \alpha + (1-\beta)z + \beta c\theta. \tag{8}$$

Reservation value for training

Training occurs as long as $J^\tau(\alpha) \geq 0$ and up to the point where the value of an untrained match is equal to the value of a trained match, that is, $J^u(\alpha_\tau) = J^\tau(\alpha_\tau)$, or:

$$y_i[\alpha_{\tau,i} - h(\alpha_{\tau,i})] = w_i^u(\alpha_{\tau,i}) - w_i^\tau(\alpha_{\tau,i}) - C(y_i \alpha_{\tau,i})$$

$$y_i[h(\alpha_{\tau,i}) - \alpha_{\tau,i}] = C(y_i \alpha_{\tau,i}) \tag{9}$$

Reservation value for hiring

The reservation value for hiring is set by the following equation $\max\{J^u(R), J^\tau(R)\} = 0$. Notice that, as long as $R < \alpha_\tau$ (and therefore some training occurs), the relevant condition can be re-written as $J^\tau(R) = 0$, or $(1-\beta)[yh(R) - C(yR)] = (1-\beta)z + \beta c\theta$.

$$yh(R) - C(yR) = z + \frac{\beta}{1-\beta} c\theta \tag{10}$$

Appendix B.5 Aggregate Shocks

Assume that sectors 1 and 2 are identical (because the assumption that sectors are identical we drop the subscript "i"), and focus on how the aggregate productivity shock p influences the decision to train. When p changes the two reservation productivity thresholds α_τ (for training decisions) and R (for hiring decisions) may also change.

From equation (9) we can see that if and how α_τ changes depends on what we assume about the functions h and C. We can therefore find appropriate functions that deliver the predictions we observe from the data. In particular, if we assume that

$$[h(\alpha) - \alpha] < \frac{\partial C(y\alpha)}{\partial y} \tag{11}$$

when overall productivity decreases, training gets more convenient because its cost decreases faster than the relative benefit and α_τ raises.

When y decreases θ should decrease as well since unemployment increases for the whole economy more than vacancies do. Therefore, the RHS of (10) decreases and the so LHS has to decrease as well. If, like in the basic Pissarided model with stochastic job matching, R should also increase, then the higher R in this case might imply lower training because relatively more workers with higher productivity and no need for training are going to be hired. (Note there is no such problem if R does not increase, or if at the same time α_τ raises sufficiently). The final effect would depend on the parametrization of the model and the choice of h and C, and as such, we can always find reasonable functions for which the first channel on α_τ prevails and generates counter-cyclical training.

Appendix B.6 Sectoral reallocation

The impact of the idiosyncratic shock ϵ_i is easier to show when we think of the adjustments that happen when one sector only, say for instance sector 2, experiences a negative shock, that is, ϵ_2 is lower. Re-proposing equation (10) for sector 1 we have,

$$y_1 h(R) - C(y_1 R) = z + \frac{\beta}{1-\beta} c\theta \tag{12}$$

The new steady state implies a higher unemployment and lower θ, adjustments through which sector 2 influences sector 1. In equation (12) the RHS is lower, and, because y_1 does not go down, the only way to re-establish the equality is by reducing R. (Also note that with no change in ϵ_1, $\alpha_{\tau,1}$ does not change, as θ does not enter in its determination.) Therefore, because the pool of workers to be trained is now larger, training will increase in sector 1.