Appendix

Outline

- Appendix A presents additional empirical results
- Appendix B presents the data in more details
- Appendix C presents the roll-out of broadband internet in France
- Appendix D presents evidence that broadband internet is skill-biased
- Appendix E presents the simple model

A Additional Results

A.1 Tables

TABLE A1. Effect of ADSL on outsourcing expenditure and occupational sorting

	(1)	(2)	(3)	(4)
	Outsourcing / wage bill		Occupational concentration (wage bill HHI)	
VARIABLES	City level	Estab. Level	City level	Estab. Level
T = 0	0.00304	0.00712	0.00128	0.00157***
	(0.00601)	(0.00446)	(0.00118)	(0.000471)
T = +1	0.0102	0.0102*	0.00418**	0.00318***
	(0.00855)	(0.00604)	(0.00162)	(0.000797)
T = +2	0.0157	0.0123	0.00693***	0.00736***
	(0.0111)	(0.00767)	(0.00196)	(0.00104)
T = +3	0.0233	0.0184*	0.00906***	0.0117***
	(0.0144)	(0.0107)	(0.00273)	(0.00145)
T = +4	0.0296	0.0210	0.00981***	0.0128***
	(0.0185)	(0.0141)	(0.00321)	(0.00168)
Average effect	0.0164	0.0138*	0.00625***	0.00733***
	(0.0109)	(0.00804)	(0.00202)	(0.000988)
Baseline mean	0.27	0.36	0.37	0.37
	(0.57)	(1.09)	(0.157)	(0.180)
Observations	293,463	1,335,364	423,770	3,077,125
R-squared	0.682	0.787	0.779	0.846

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. Columns (1) and (3) run the regression at the city level, following equation 3, where the dependent variables are the weighted average of the firm outcomes at the city level, and controls are the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level. Columns (2) to (4) run the same specification on the outcome computed at the establishment level, replacing city fixed effects by establishment fixed effects.

TABLE A2. Effect of ADSL on high and low-skill outsourcing

	(1)	(2)	(3)	(4)
	High-skill outsourcing		Low-skill outsourcing	
	Sh. of empl. in HS outs. services	Sh. outs. workers in HS outs. services	Sh. of empl. in LS outs. services	Sh. outs. workers in LS outs. services
T = 0	0.00150***	0.00539***	0.00142	0.00843**
	(0.000518)	(0.00189)	(0.00101)	(0.00359)
T = +1	0.00204***	0.00766**	0.00210	0.00799
	(0.000637)	(0.00293)	(0.00149)	(0.00518)
T = +2	0.00291***	0.0115**	0.00370*	0.0226***
	(0.000816)	(0.00465)	(0.00203)	(0.00596)
T = +3	0.00357***	0.0164***	0.00615**	0.0358***
	(0.00122)	(0.00576)	(0.00267)	(0.00735)
T = +4	0.00394**	0.0134	0.0106***	0.0347***
	(0.00159)	(0.00839)	(0.00334)	(0.00929)
Average effect	0.00279***	0.0109**	0.00479**	0.0219***
	(0.000884)	(0.00438)	(0.00198)	(0.00559)
Baseline mean	0.017	0.065	0.103	0.184
	(0.087)	(0.193)	(0.240)	(0.336)
Observations	423,770	164,880	423,770	188,496
R-squared	0.821	0.727	0.902	0.798

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. The regressions are run at the city level following equation 3. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level.

TABLE A3. Effect of ADSL on share of employment in outsourcing services by sub-category

	(1)	(2)	(3)	(4)	(5)	(6)
	Sh. of empl. in HS outs. Services		Sh. of empl. in LS outs. Services			
	IT services	Consulting, advertising & HR services	Security services	Cleaning services	Driving services	Logistics services
T = 0	0.000451	0.00105***	-0.000145	0.000467	0.00120	-0.000104
	(0.000297)	(0.000395)	(0.000265)	(0.000301)	(0.000914)	(0.000319)
T = +1	0.000615	0.00142***	-0.000371	0.000435	0.00187	0.000169
	(0.000372)	(0.000489)	(0.000387)	(0.000453)	(0.00141)	(0.000479)
T = +2	0.000803	0.00211***	-0.000290	0.000905	0.00246	0.000627
	(0.000513)	(0.000609)	(0.000550)	(0.000565)	(0.00190)	(0.000655)
T = +3	0.000975	0.00259***	-0.000309	0.00232***	0.00371	0.000427
	(0.000684)	(0.000888)	(0.000705)	(0.000692)	(0.00250)	(0.000884)
T = +4	0.00114	0.00280**	-9.28e-06	0.00329***	0.00631**	0.000976
	(0.000902)	(0.00111)	(0.000862)	(0.000857)	(0.00313)	(0.00116)
Average effect	0.000798	0.00200***	-0.000225	0.00148***	0.00311*	0.000419
	(0.000525)	(0.000624)	(0.000522)	(0.000514)	(0.00186)	(0.000671)
Baseline mean	0.004	0.013	0.004	0.010	0.082	0.007
	(0.041)	(0.076)	(0.044)	(0.073)	(0.222)	(0.056)
Observations	423,770	423,770	423,770	423,770	423,770	423,770
R-squared	0.827	0.814	0.796	0.860	0.909	0.845

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. The regressions are run at the city level following equation 3. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level.

TABLE A4. Effect of ADSL on share of outs. workers in outsourcing services by sub-category

	(1)	(2)	(3)	(4)	(5)	(6)
	Sh. outsourceable workers in HS outs. Services		Sh. outsourceable workers in LS outs. Services			
	IT specialists in IT services	Admin, sales and HR specialists in consulting, advertising & HR services	Security guards in security services	Cleaners in cleaning services	Drivers in driving services	Maintenance and warehouse workers in logistics services
T = 0	0.0121***	0.00481***	0.0290***	0.0373***	0.0103***	-0.00151
	(0.00381)	(0.00182)	(0.00702)	(0.00469)	(0.00383)	(0.00209)
T = +1	0.0211***	0.00690**	0.0505***	0.0652***	0.00837	-0.00241
	(0.00609)	(0.00300)	(0.0108)	(0.00620)	(0.00545)	(0.00356)
T = +2	0.0305***	0.0105**	0.0880***	0.0990***	0.0110	-0.00199
	(0.00839)	(0.00455)	(0.0144)	(0.00855)	(0.00736)	(0.00523)
T = +3	0.0327***	0.0157***	0.133***	0.128***	0.0159*	-0.00516
	(0.0122)	(0.00578)	(0.0197)	(0.0120)	(0.00911)	(0.00711)
T = +4	0.0337*	0.0141*	0.143***	0.158***	0.00406	-0.00760
	(0.0186)	(0.00831)	(0.0284)	(0.0152)	(0.0122)	(0.00950)
Average effect	0.0260***	0.0104**	0.0888***	0.0974***	0.00992	-0.00373
	(0.00909)	(0.00436)	(0.0137)	(0.00855)	(0.00672)	(0.00533)
Baseline mean	0.088	0.047	0.143	0.094	0.193	0.033
	(0.244)	(0.161)	(0.328)	(0.272)	(0.360)	(0.152)
Observations	56,593	162,706	28,422	89,278	129,649	134,260
R-squared	0.793	0.715	0.823	0.756	0.824	0.803

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. The regressions are run at the city level following equation 3. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level.

TABLE A5. Descriptive statistics of the share of mobilities going to connected cities

	High Skill workers		Low Skill workers	
Year	Movements to outsourcing	Movements to non-outsourcing	Movements to outsourcing	Movements to non-outsourcing
2000	23%	34%	23%	25%
2001	63%	86%	63%	67%
2002	82%	93%	81%	84%
2003	88%	95%	88%	89%
2004	92%	98%	92%	93%
2005	97%	99%	95%	97%
2006	99%	99%	99%	99%

Notes: Summary statistics computing the share of mobility towards both the outsourcing and non-outsourcing sectors that has for destination a city that is already connected by broadband internet.

TABLE A6. Average wage and employment in outsourceable occupations across sectors

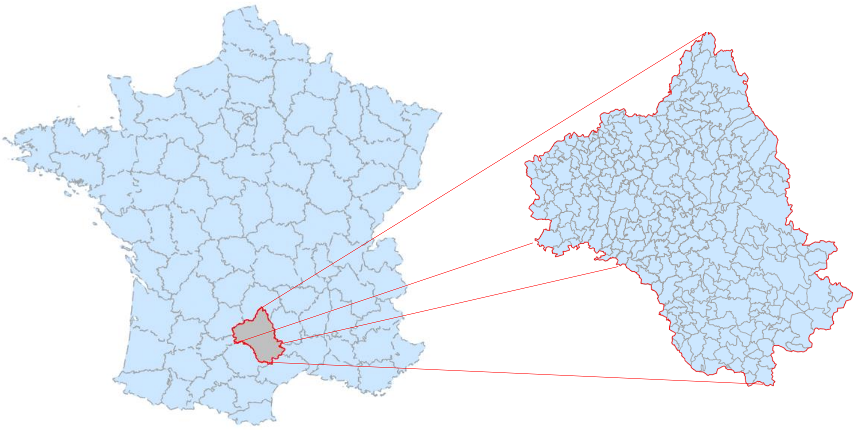
		outsourcing services	Other services	Manufacturing
		mean/(sd)	mean/(sd)	mean/(sd)
Gross hourly wage workers in HS outsourceable occup. (2010 euros)	overall	30.7	24.8	28.6
		(13.2)	(11.9)	(12.2)
	pre-BI	29.6	22.6	27.1
		(11.7)	(10.7)	(9.2)
	post-BI	31.1	26.0	29.8
		(13.6)	(12.3)	(13.9)
N. of workers in HS outsourceable occup. Per establishment	overall	179.1	42.1	69.5
		(414.6)	(145.4)	(211.7)
	pre-BI	196.7	48.6	65.0
		(369.9)	(154.4)	(188.7)
	post-BI	173.3	38.7	73.0
		(428.2)	(140.4)	(228.0)
Gross hourly wage workers in LS outsourceable occup. (2010 euros)	overall	12.1	13.4	15.3
		(3.4)	(3.9)	(4.8)
	pre-BI	11.6	12.7	14.5
		(3.4)	(3.7)	(3.9)
	post-BI	12.3	13.9	16.1
		(3.4)	(4.0)	(5.2)
N. of workers in LS outsourceable occup. per establishment	overall	154.0	23.7	50.5
		(277.2)	(58.7)	(161.9)
	pre-BI	154.3	27.1	56.7
		(279.0)	(51.2)	(172.8)
	post-BI	153.9	21.6	45.1
		(276.4)	(62.9)	(151.8)

Notes: Summary statistics comparing wages and employment of outsourceable workers (high-skill and low-skill) across different sectors.

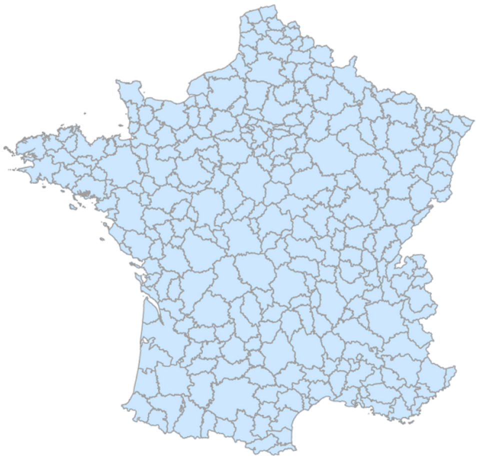
A.2 Figures

FIGURE A1. Departments, commuting zones and cities in France

(a) Departments and cities

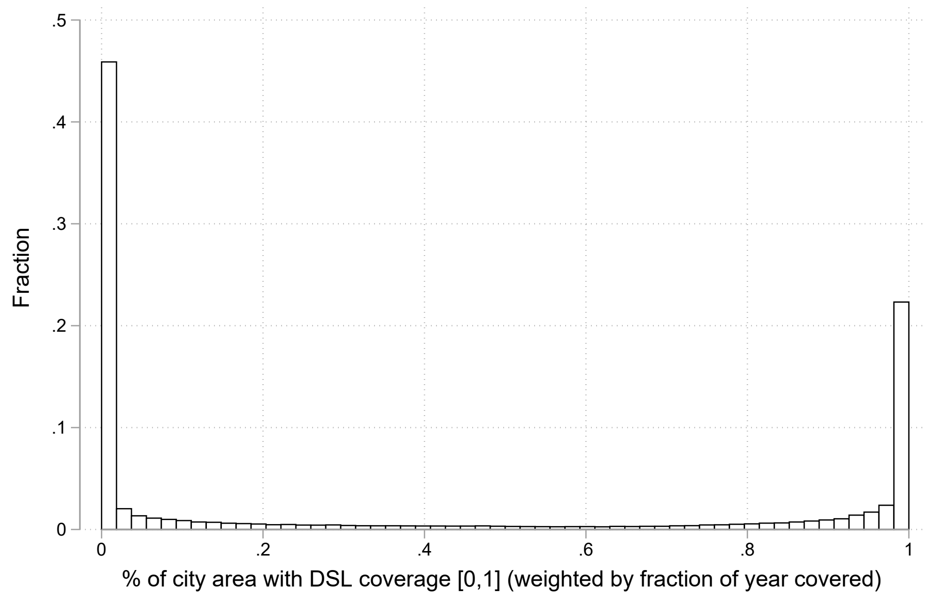


(b) Commuting Zones



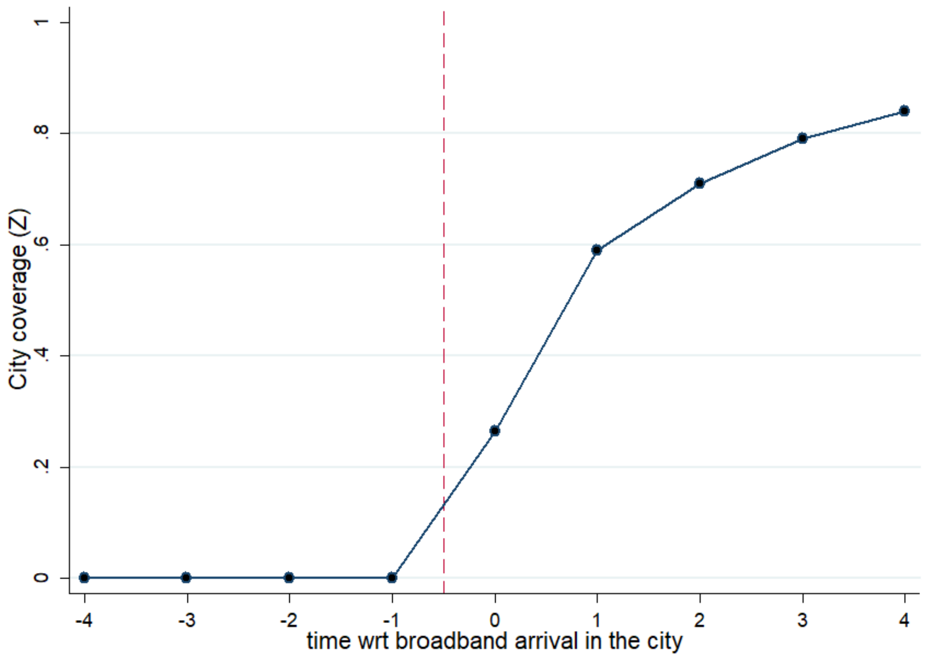
Notes: The first map represents the distribution of departments ("départements") in France and takes the example of Aveyron (department number 12) to show the distribution in cities. The second map represents the distribution of Commuting Zones ("Zones d'emploi").

FIGURE A2. Distribution of $\widetilde{Z}_{it}$: 1999-2007



Notes: This figure plots the distribution of the continuous measure of local broadband availability (variable $\widetilde{Z}$) as defined in Equation (1). We see that while the measure is continuous and contained between 0 and 1 but presents point of accumulation on 0 and 1.

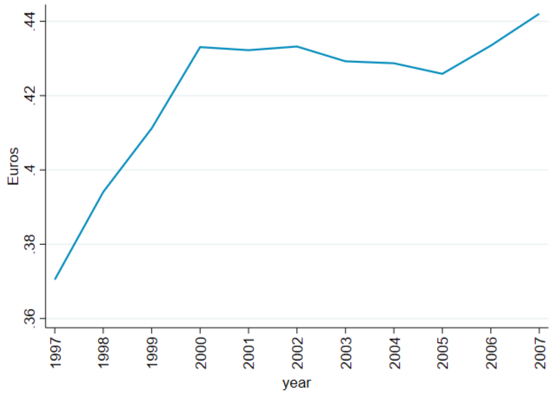
FIGURE A3. Evolution of $\widetilde{Z}_{it}$ before and after the discrete event



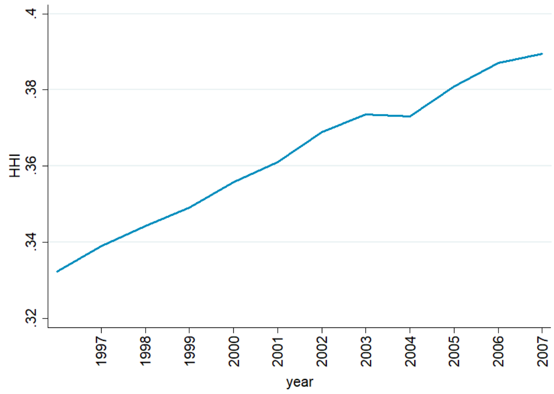
Notes: This figure plots the average of the continuous measure of local broadband availability (variable $\widetilde{Z}$) along the time to event variable, where event is the first year where $\widetilde{Z} > 0$.

FIGURE A4. Overall trends in outsourcing expenditure and occupation concentration

(a) Outsourcing expenditure over wage bill



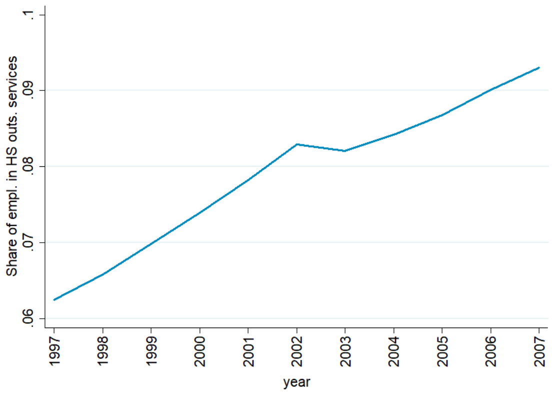
(b) Occup. concentration (HHI over wage bill)



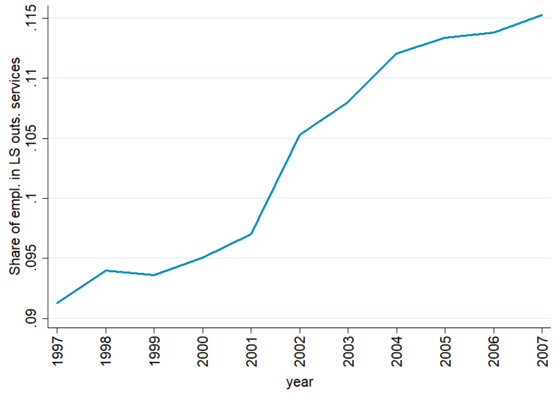
Notes: This Figure shows the evolution over time of the main outcomes of interest in the outsourcing analysis.

FIGURE A5. Overall trends in high and low skill outsourcing

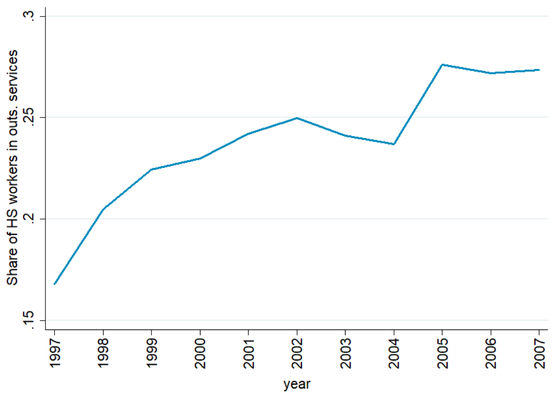
(a) Share of employment in HS outs. services



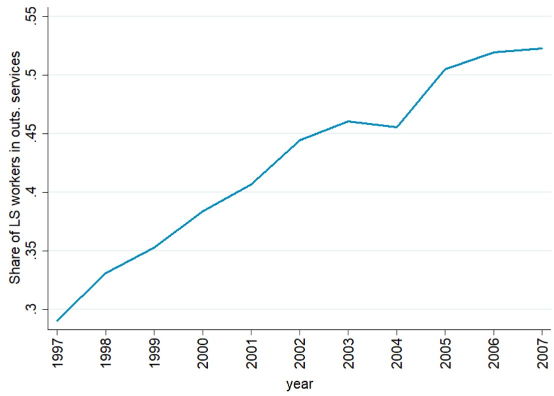
(b) Share of employment in LS outs. services



(c) Share of outs. workers in HS outs. services



(d) Share of outs. workers in LS outs. services

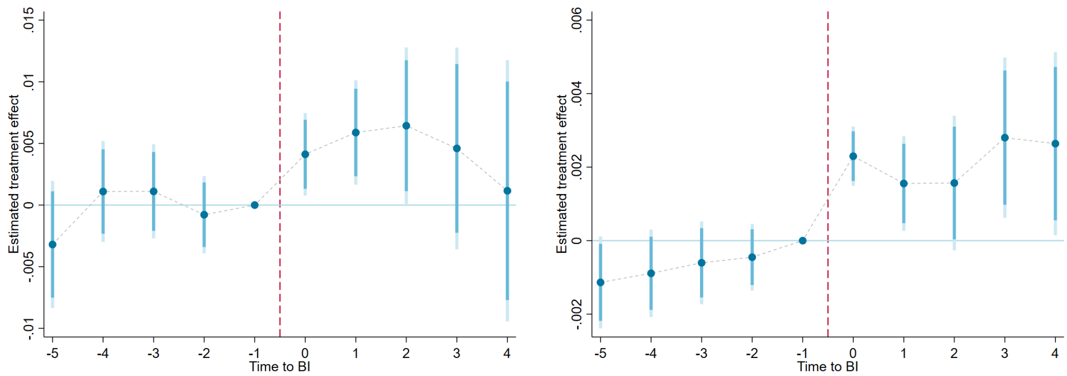


Notes: This Figure shows the evolution over time of the main outcomes of interest in the outsourcing analysis.

FIGURE A6. Share of workers moving to outsourcing firms at the city level

(a) High Skill Workers

(b) Low Skill Workers



Notes: This Figure shows regression coefficients and 90% and 95% confidence intervals from a dynamic event study where the dependent variable is the share of workers moving to an outsourcing firms within a city (respectively for high skill and low skill segments) at t and the specification follows equation (3). Observations are weighted by population in 1990.

A.3 Identification

TABLE A7. Effect of ADSL on outsourcing outcomes - static regressions

	Outsourcing / wage bill	wage bill HHI	Sh. of empl. in HS outs. services	Sh. outs. workers in HS outs. services	Sh. of empl. in LS outs. services	Sh. Outs. workers in LS outs. services
Panel A : city level regressions						
Post ADSL * treated	0.00867	0.00336**	0.00200***	0.00707***	0.00201	0.0103**
	(0.00744)	(0.00144)	(0.000573)	(0.00250)	(0.00131)	(0.00408)
Observations	293,463	423,770	423,770	164,880	423,770	188,496
R-squared	0.682	0.779	0.821	0.727	0.902	0.798
Panel B : establishment level regressions						
Post ADSL * treated	0.00925*	0.00284***	-	-	-	-
	(0.00519)	(0.000609)	-	-	-	-
Observations	1,335,364	3,077,125	-	-	-	-
R-squared	0.787	0.846	-	-	-	-

Notes: The regressions are run at the city and establishment level following a model similar to equation 3, but where instead of including the dynamic post-BI effects for every year, we just include a dummy for post-BI period interacted with the treatment indicator. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. ***, ** and * respectively denote significance at the 1, 5 and 10% level.

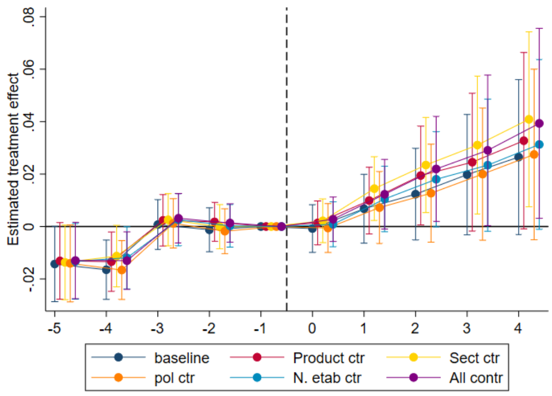
TABLE A8. Effect of ADSL on outsourcing outcomes - regressions at the labor market area level

	(1) Outsourcing / wage bill	(2) Occup. concentration (wage bill HHI)	(3) Sh. of empl. in HS outs. services	(4) Sh. Outs. workers in HS outs. services	(5) Sh. of empl. in LS outs. services	(6) Sh. outs. workers in LS outs. services
T = 0 x Zemp coverage	0.00183	4.02e-05	0.000825	0.00283	0.00381	0.0261
	(0.0350)	(0.00395)	(0.00188)	(0.0239)	(0.00330)	(0.0273)
T = +1 x Zemp coverage	0.0304	-0.00154	0.00102	0.0115	-0.00128	0.000544
	(0.0213)	(00297)	(0.00154)	(0.0160)	(0.00235)	(0.0235)
T = +2 x Zemp coverage	0.0557***	0.00315	0.00237	0.00846	0.000151	0.0461
	(0.0210)	(0.00387)	(0.00246)	(0.0209)	(0.00366)	(0.0345)
T = +3 x Zemp coverage	0.0487**	0.00923**	0.00534*	0.0358	-0.000332	0.141***
	(0.0223)	(0.00463)	(0.00302)	(0.0277)	(0.00467)	(0.0461)
T = +4 x Zemp coverage	0.0453	0.0161***	0.00788**	0.0468	-0.000565	0.199***
	(0.0297)	(0.00527)	(0.00370)	(0.0344)	(0.00653)	(0.0490)
Average effect	0.0364*	0.0054	0.00349	0.0211	0.000356	0.0825***
	(0.0202)	(0.00363)	(0.0022)	(0.0190)	(0.00356)	(0.0291)
Observations	2,880	2,783	2,783	2,783	2,783	2,783
R-squared	0.815	0.891	0.974	0.809	0.952	0.810

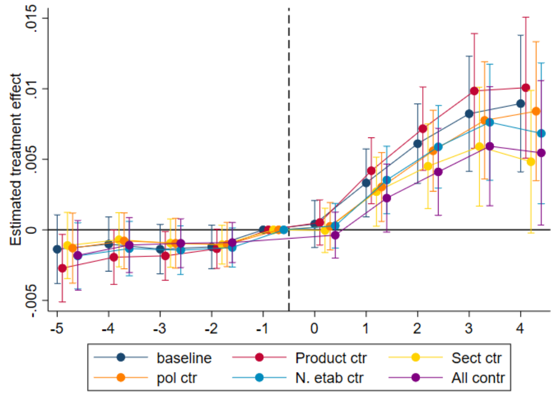
Notes: The regressions are run at the labor market area (*Zone d'emploi*) level. Given that there is little variation in the timing of first BI appearance in labor market areas within the same department, we take advantage of the continuous measure of BI coverage: we estimate a standard staggered model similar to equation 2, but where we interact the dynamic post-BI dummies for every year with the share of the labor market area that is covered in that period. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, and labor market area fixed effects. ***, ** and * respectively denote significance at the 1, 5 and 10% level.

FIGURE A7. Robustness of city-level results: adding additional controls

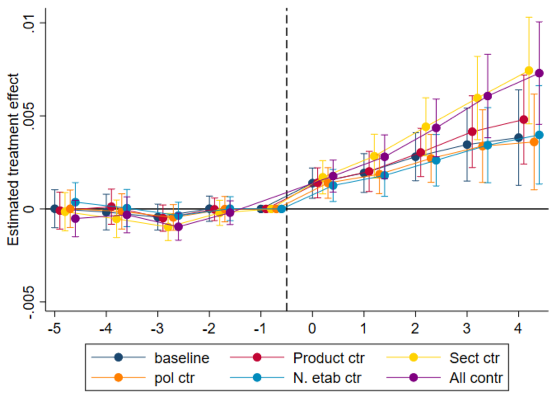
(a) Outsourcing/wage bill



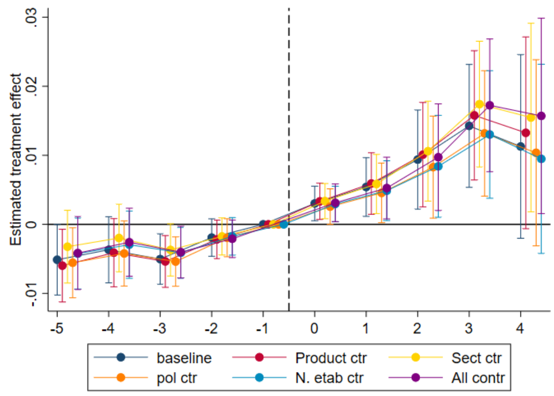
(b) Occup. concentration (HHI)



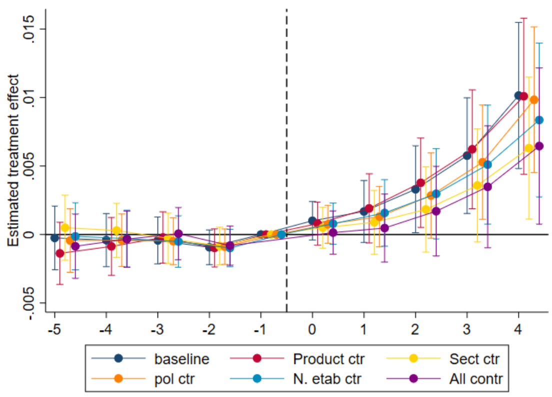
(c) Sh. of empl. in HS outs. services



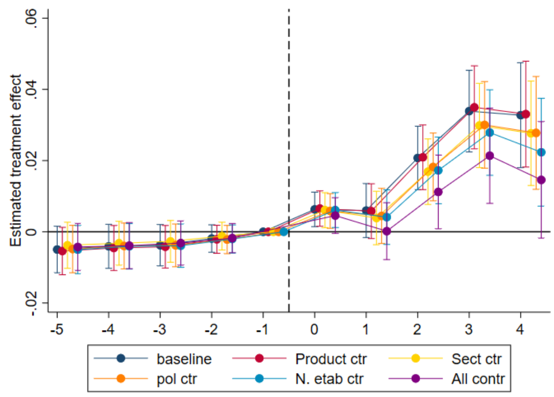
(d) Sh. outs. workers in HS outs. services



(e) Sh. of empl. in LS outs. services



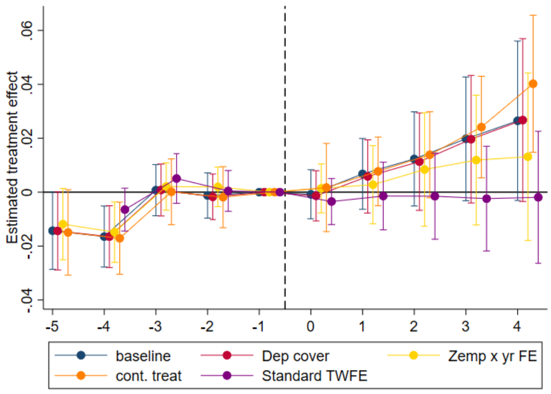
(f) Sh. outs. workers in LS outs. services



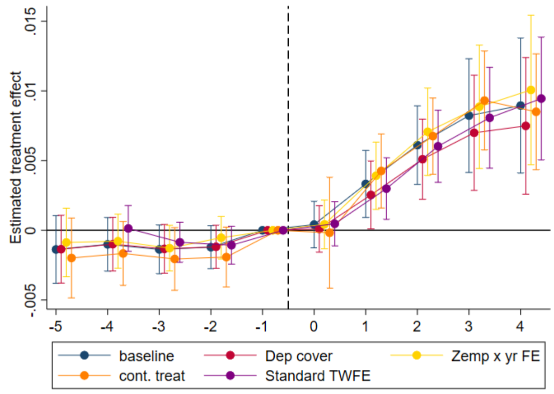
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating equation (3) on city-level data with different sets of controls. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level. The navy blue line shows the baseline model that we use in the main analysis for comparison. The red line adds controls for the productivity growth observed in each city between 1996 and 1998, interacted with year dummies. The yellow line adds controls for the sectoral composition in each city prior to 1999 interacted with year fixed effects. The orange line adds controls for the share of left-wing votes in the presidential election of 1995 interacted with year dummies and a dummy for wether there was a change in majority between 1995 and 2002, also interacted with year dummies. The light blue line controls for city size prior to 1999, measured as the number of establishments active in the city, interacted with year fixed effects. Finally, the purple line adds all the controls at once.

FIGURE A8. Robustness of city-level results: other robustness tests

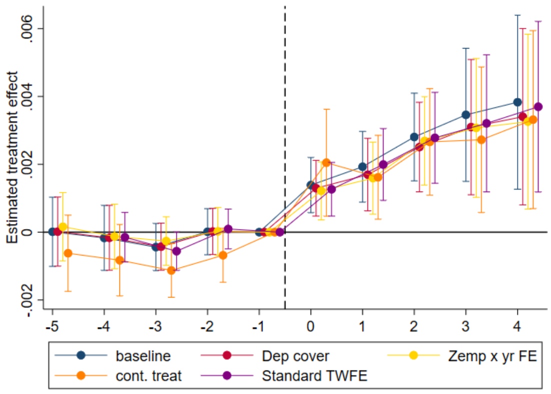
(a) Outsourcing/wage bill



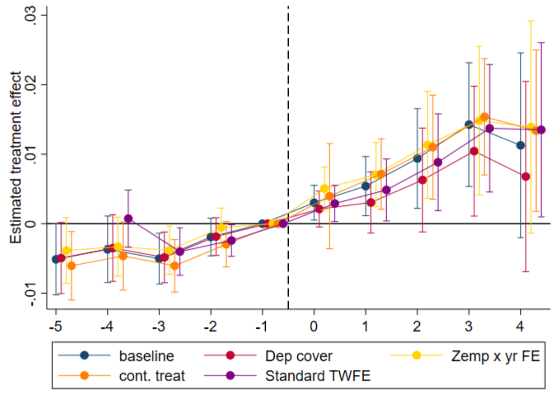
(b) Occup. concentration (HHI)



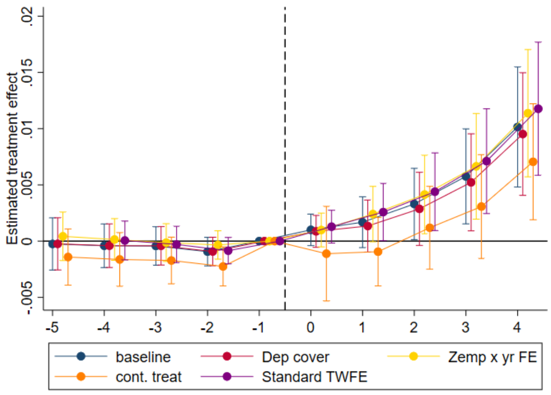
(c) Sh. of empl. in HS outs. services



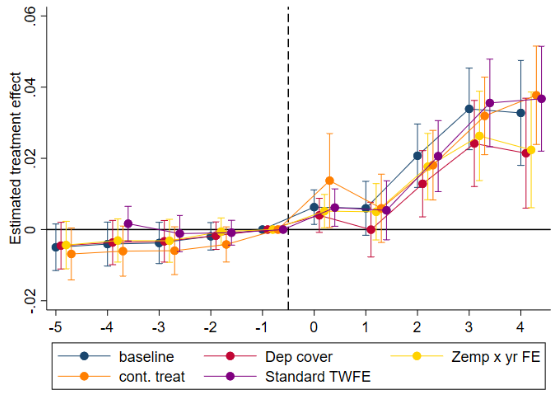
(d) Sh. outs. workers in HS outs. services



(e) Sh. of empl. in LS outs. services

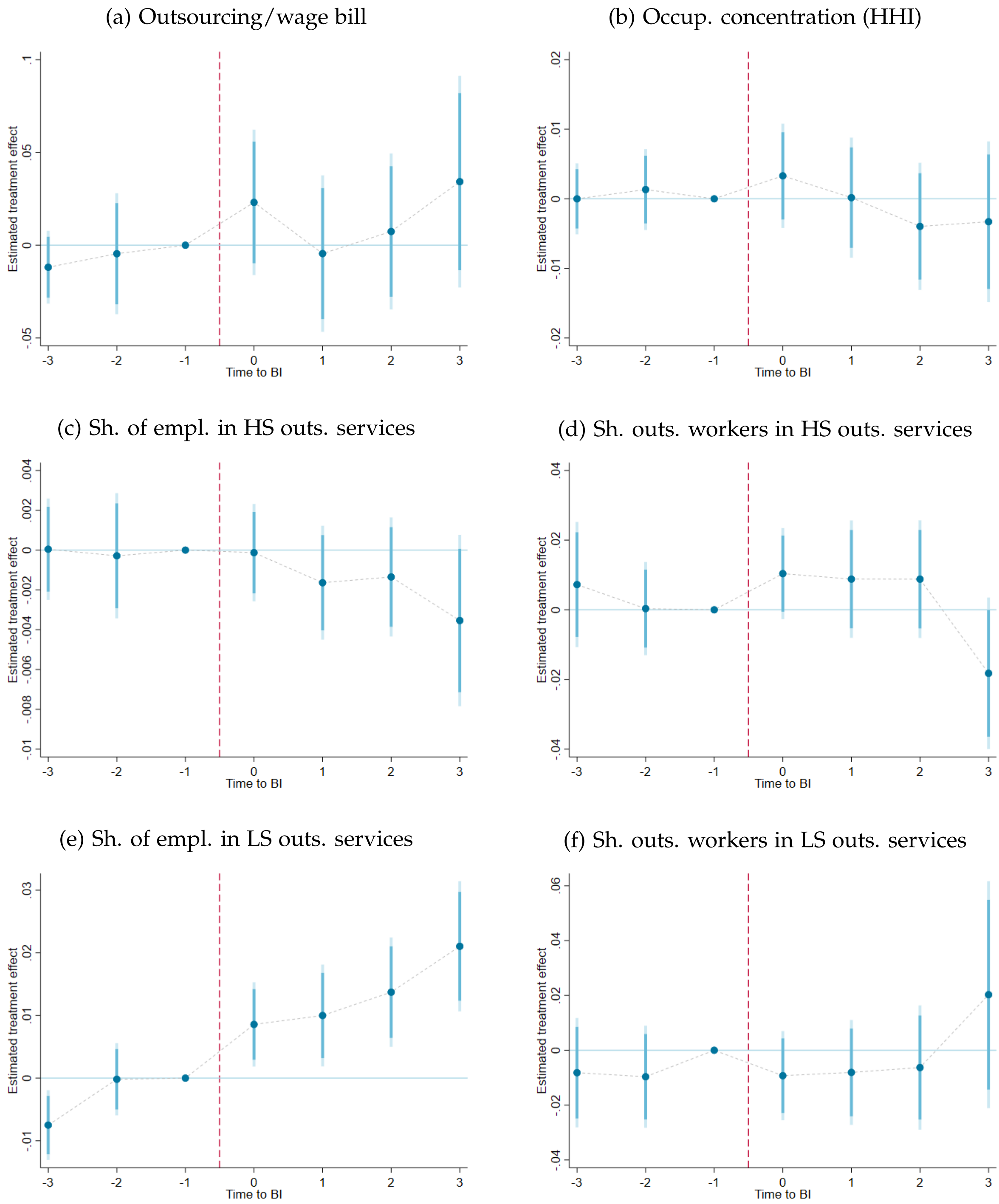


(f) Sh. outs. workers in LS outs. services



Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating slightly different models. All models control for the population density in 1999 interacted with year dummies, department $\times$ year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level. The blue line shows the baseline model that we use in the main analysis for comparison. The red line adds a control for the BI coverage observed in the other cities within the same department. The yellow line shows the results obtained after replacing the department $\times$ year fixed effects with commuting zone $\times$ year fixed effects. The orange line shows the results obtained while using the continuous measure of treatment $\tilde{Z}_i t$ instead of the binary indicator. The purple line shows the results obtained from running a standard staggered difference-in-differences model as in equation 2.

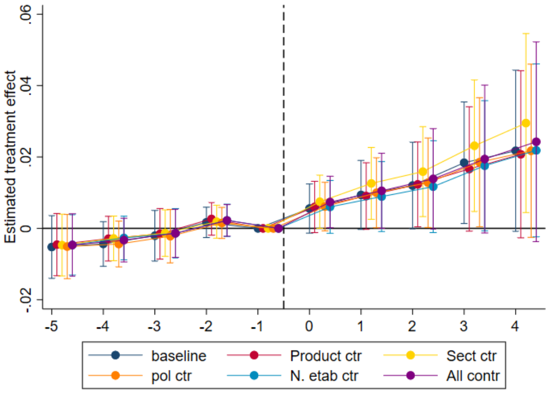
FIGURE A9. Robustness of city-level results: Placebo tests



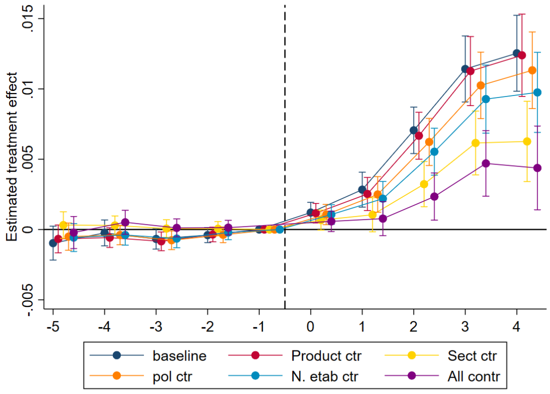
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from placebo regressions. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level. Late receivers of broadband (2004 to 2007) are split into high (HPLR) and low propensity (LPLR) to be early receivers based on the propensity score. The HPLR are assigned to the pseudo-treatment year computed as the actual year of treatment - 4. The graph presents the pseudo-treatment effect observed over the period where none of the cities in the sample is actually treated (1997 to 2003).

FIGURE A10. Robustness of establishment-level results: adding additional controls

(a) Outsourcing/wage bill



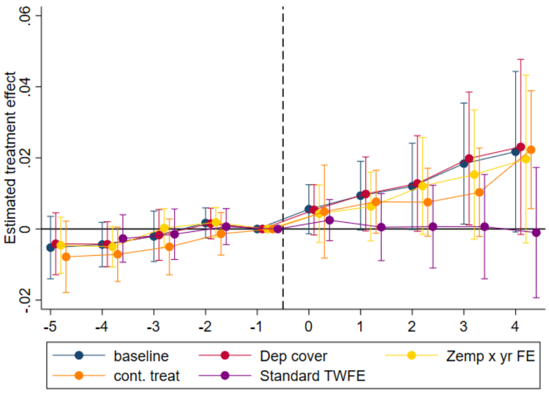
(b) Occup. concentration (HHI)



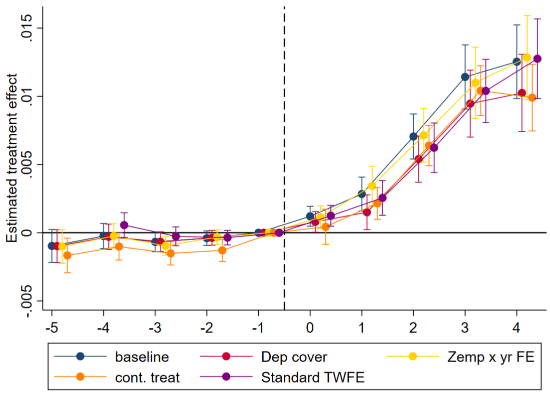
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating equation (3) on establishment-level data with different sets of controls. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, establishment fixed effects and sample fixed effects. Standard errors are clustered at the department level.The navy blue line shows the baseline model that we use in the main analysis for comparison. The red line adds controls for the productivity growth observed in each city between 1996 and 1998, interacted with year dummies. The yellow line adds controls for the sectoral composition in each city prior to 1999 interacted with year fixed effects. The orange line adds controls for the share of left-wing votes in the presidential election of 1995 interacted with year dummies and a dummy for wether there was a change in majority between 1995 and 2002, also interacted with year dummies. The light blue line controls for city size prior to 1999, measured as the number of establishments active in the city, interacted with year fixed effects. Finally, the purple line adds all the controls at once.

FIGURE A11. Robustness of establishment-level results: other robustness tests

(a) Outsourcing/wage bill



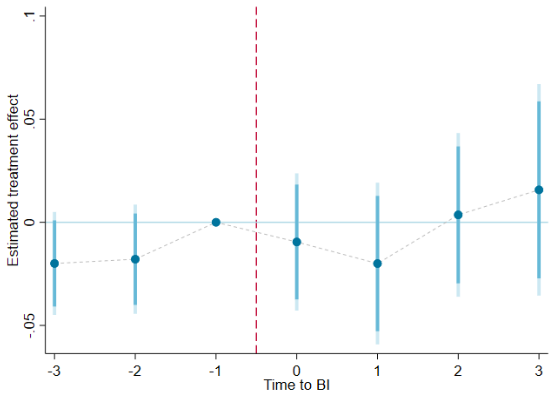
(b) Occup. concentration (HHI)



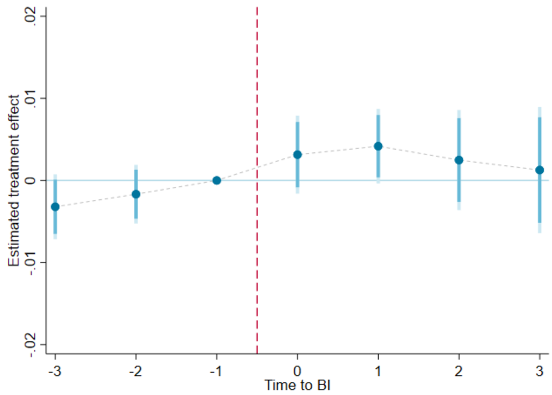
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating slightly different models. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, establishment fixed effects and sample fixed effects. Standard errors are clustered at the department level. The blue line shows the baseline model that we use in the main analysis for comparison. The red line adds a control for the BI coverage observed in the other cities within the same department. The yellow line shows the results obtained after replacing the department × year fixed effects with commuting zone × year fixed effects. The orange line shows the results obtained while using the continuous measure of treatment $\tilde{Z}_i t$ instead of the binary indicator. The purple line shows the results obtained from running a standard staggered difference-in-differences model as in equation 2.

FIGURE A12. Robustness of establishment-level results: Placebo tests

(a) Outsourcing/wage bill



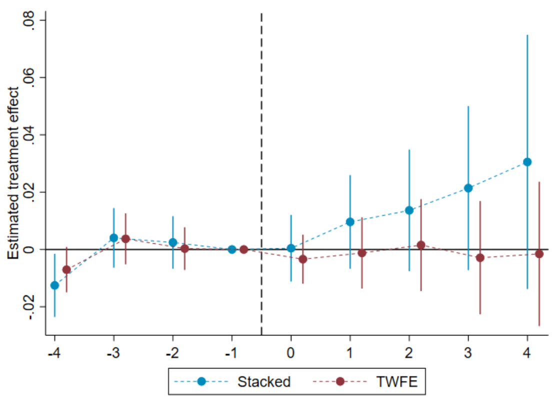
(b) Occup. concentration (HHI)



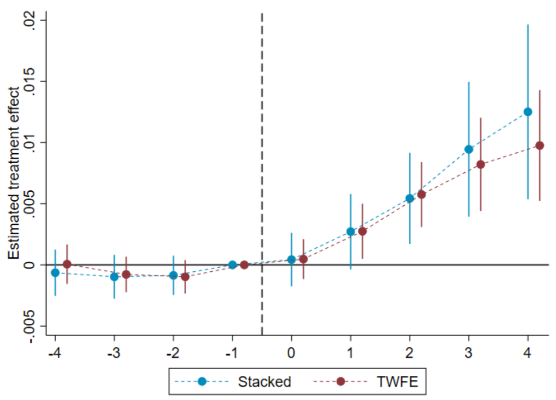
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating slightly different models. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, establishment fixed effects and sample fixed effects. Standard errors are clustered at the department level. Late receivers of broadband (2004 to 2007) are split into high (HPLR) and low propensity (LPLR) to be early receivers based on the propensity score. The HPLR are assigned to the pseudo-treatment year computed as the actual year of treatment - 4. The graph presents the pseudo-treatment effect observed over the period where none of the cities in the sample is actually treated (1997 to 2003).

FIGURE A13. Event study graphs at the city level using cohorts treated in 2005-2007 as pure controls

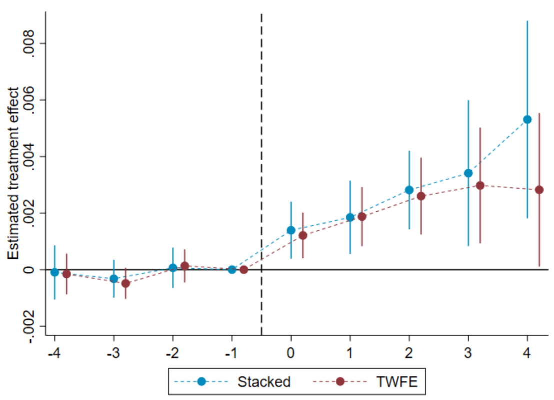
(a) Outsourcing/wage bill



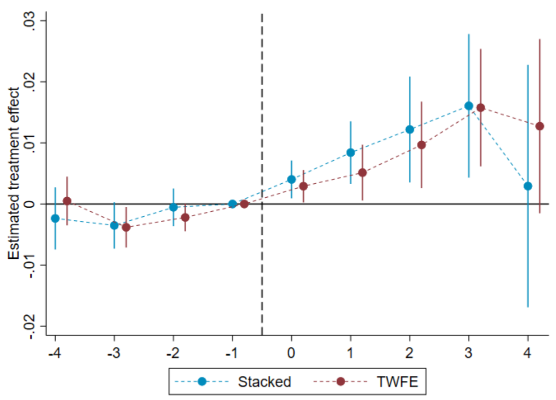
(b) Occup. concentration (HHI)



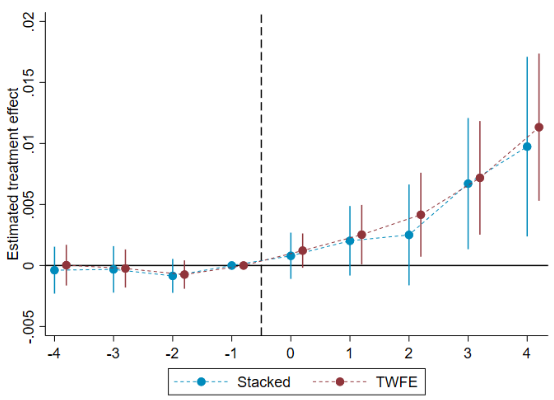
(c) Sh. of empl. in HS outs. services



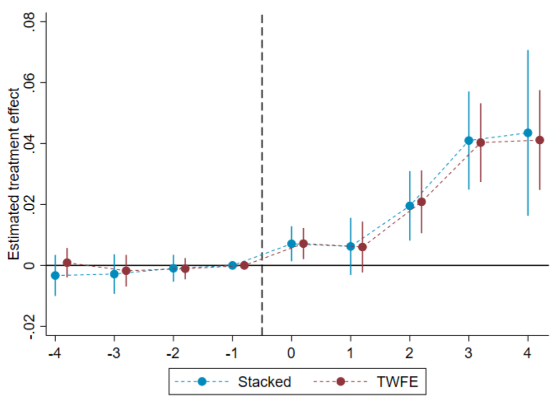
(d) Sh. outs. workers in HS outs. services



(e) Sh. of empl. in LS outs. services

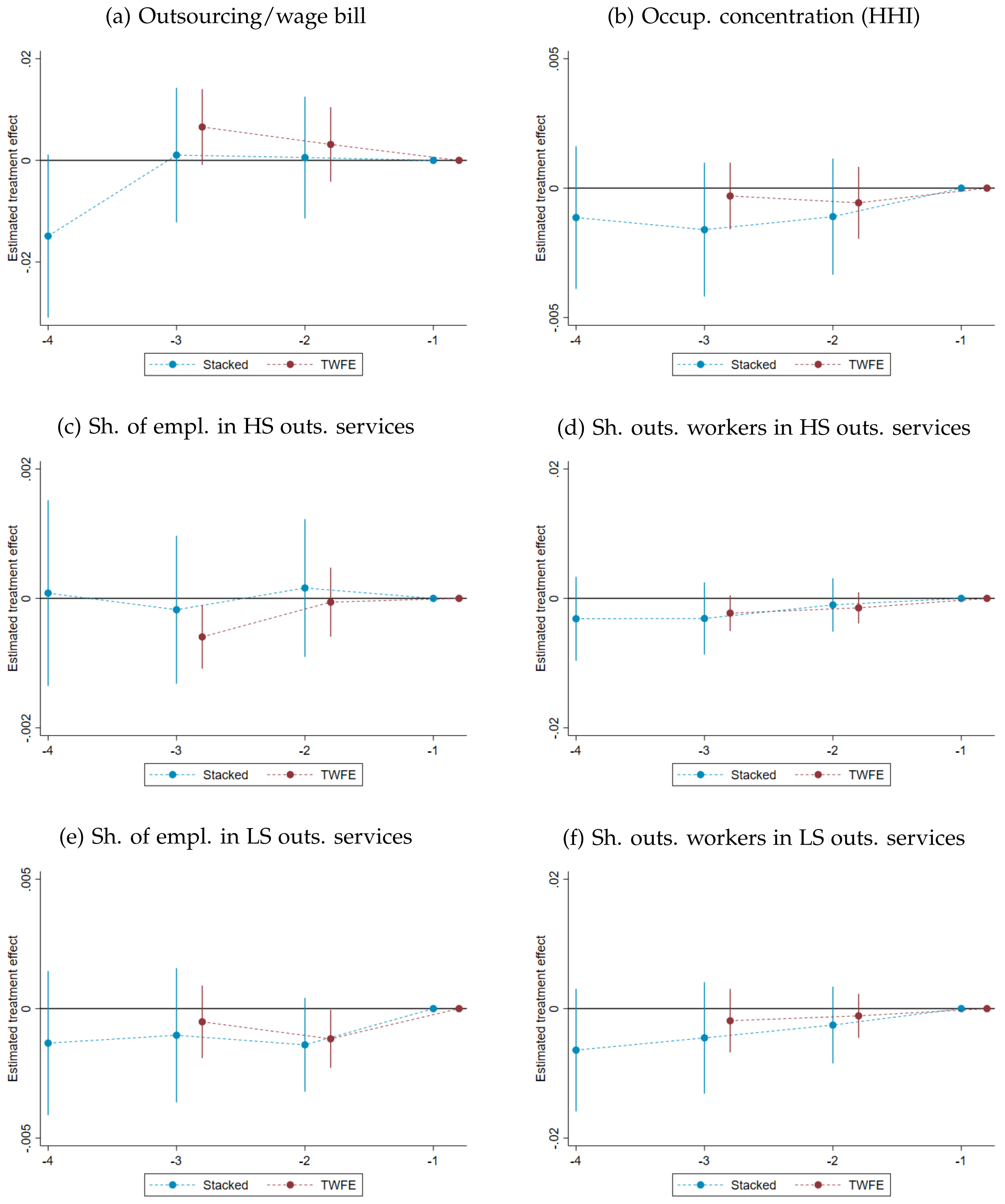


(f) Sh. outs. workers in LS outs. services



Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating equations (2) (TWFE) and (3) (Stacked) on city-level data for the years 1997 to 2004. As such, the cohorts treated between 2005 and 2007 serve as pure controls since they are never treated over this period. All models control for the population density in 1999 interacted with year dummies, department $\times$ year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level.

FIGURE A14. Additional pre-trend tests for the city level results



Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating equations (2) (TWFE) and (3) (Stacked) on city-level data for the period preceding treatment (the data is cut at T-1 relative to treatment). The stacked model allows to estimate one additional pre-period dummy relative to the TWFE model. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level.

B Data Appendix: Administrative Employer-Employee Data

Our main analysis relies on data from the administrative records used by the French government to compute payroll taxes. Our period of analysis spans from 1996 to 2007. The first year is chosen to include a few years prior to the beginning of broadband diffusion, which started in 1999, while the last year corresponds to the final year of broadband expansion. We chose not to include later years because of the effect of the financial crisis. These data are collected yearly by *INSEE* (the French statistics office) and are known as *DADS* ("Déclarations annuelles des données sociales"). The main dataset contains information on all existing work contracts for each establishment in each firm operating in the French territory. The latter allows us to monitor establishments and firms over time but not workers, with the exception of a one-year worker panel dimension available since 2002. This is the main source that we use for the city and firm-level analyses. For the worker-level analysis, we rely on a subsample of this data from the DADS Panel. The latter randomly selects 1/24 of the labor force and follows it across its employment over the entire period. The random selection is achieved through the inclusion of all workers born in October of an even year. The raw data provided to researchers has already undergone substantial verification, and consequently only requires a minimal amount of additional cleaning. For this study, we focus on workers with some degree of attachment to the labor market ("postes non-annexes"), which are defined as contracts involving either more than 120 hours of work or more than 30 days of work, with more than 1.5 hours of work per day, or contracts that paid more than 3 times the monthly minimum wage over the year. We also exclude firms with less than 10 employees, to avoid taking family-run companies into consideration and thus focus on formal businesses. We further exclude some occupations and industries since we are interested only in the private sector. In the following bullet points we specify the excluded occupations by their PCS-2003 classification codes and the excluded industries based on the NAF rev. 1 classification. Given that both of these classifications changed in the middle of our sample (2002), we use official crosswalk tables to identify the same groups between years.

- **Selection of occupations:** We exclude all categories of non-employed people OA-11 (cs 2 [7, 9]) and self-employed farmers (pcs = 1). We further exclude self-employed crafts workers (pcs = 20), liberal professions (pcs = 31), university professors (pcs = 34), school teachers (pcs = 42) and the clergy (pcs = 44).

- **Selection of industries:** We exclude mining and farming ($NAF \in [1, 9]$), utilities ($NAF \in [35, 39]$), the entire public sector ($NAF \in [84, 88]$), and social services ($NAF \geq 90$).

- **High-skill workers**: We define high-skill workers as those belonging to the category including CEOs and the category including executives, managers and engineers (pcs = 2 and pcs = 3).

Once this cleaning is completed, we define the main categories used in the outsourcing analysis as reported in Table B1. For the low skill categorization we follow the categories proposed by Goldschmidt and Schmieder (2017), but we exclude food services because in the PCS classification of occupations it is impossible to distinguish canteen workers from the much larger category of waiters and restaurant workers. The remaining ones are security, cleaning, driving and logistics. For the high-skill categorization we base ourselves on the two largest industry categories that provide professional services to other firms: IT and consulting (which includes strategy consulting, HR and advertising).

As mentioned in the body of the text, the DADS do not contain information on education. Therefore, high and low-skill are based on intuitive interpretation of the occupational code. Nevertheless, in order to validate the final classification, we use additional survey data in order to assess whether the occupation codes that we use to define skill levels are strongly correlated or not with the level of education attained. To show this we computed some statistics based on the French Labor Force Survey, which includes both dimensions. In Table B2 we see that overall in the French labor market 19% of workers have less than a high-school degree, 58% have a high-school diploma, and 23% have more than a high-school degree. Among executives (used to measure skill-biased technical change in Appendix D) and among high-skill outsourceable occupations, only 3-4% have less than a high-school degree and 60% or more have more than a high-school degree. On the contrary, among low-skill outsourceable occupations 32% have less than a high-school degree and only 8% have more. Overall it appears that the occupations we chose, while conceptually distinct from formal education, correlate strongly with form education attainment.

TABLE B1. Categorization of outsourceable occupations and outsourcing sectors

High-Skill Outsourcing		
	Outsourcing sectors	sub-category
NAF = 72	IT services	IT
NAF = 74.1	Admin services, management consulting	consulting
NAF = 74.4	Advertising	consulting
NAF = 74.5	HR services	consulting
	Outsourceable occupations	sub-category
PCS = 388	IT engineers	IT
PCS = 478	IT technicians	IT
PCS = 372	HR executives	consulting
PCS = 373	Admin. Executives	consulting
PCS = 461	Admin. Support staff	consulting
PCS = 375	Advertising executives	consulting
PCS = 464a	Advertising and PR support staff	consulting
Low-Skill Outsourcing		
	Outsourcing sectors	sub-category
NAF = 74.6	Security	security
NAF = 74.7	Cleaning	cleaning
NAF = 60.2	urban and road transportation	driving
NAF = 63.1	Maintenance and storage	logistics
NAF = 63.4	Logistics of merchandise transportation	logistics
	Outsourceable occupations	sub-category
PCS = 533, 534	Security guards	security
PCS = 684	Cleaners	cleaning
PCS = 641a	Road drivers	driving
PCS = 643a	Delivery personnel	driving
PCS = 651	Storage machine operator	logistics
PCS = 652	Maintenance worker	logistics
PCS = 653	Warehouse workers	logistics

Notes: List of outsourcing sectors providing services to other firms, and of outsourceable occupations that are employed by them. We broadly categorize them into high- and low-skill services, where the first includes IT and consulting activities, while the second includes security, cleaning, driving and logistics.

TABLE B2. Distribution of education levels across occupation categories

	Less than high-school degree	High-school degree	More than high-school degree
Across all occupations	19%	58%	23%
Executives	4%	30%	66%
High-skill outsourceable occup.	3%	37%	60%
Low-skill outsourceable occup.	32%	60%	8%

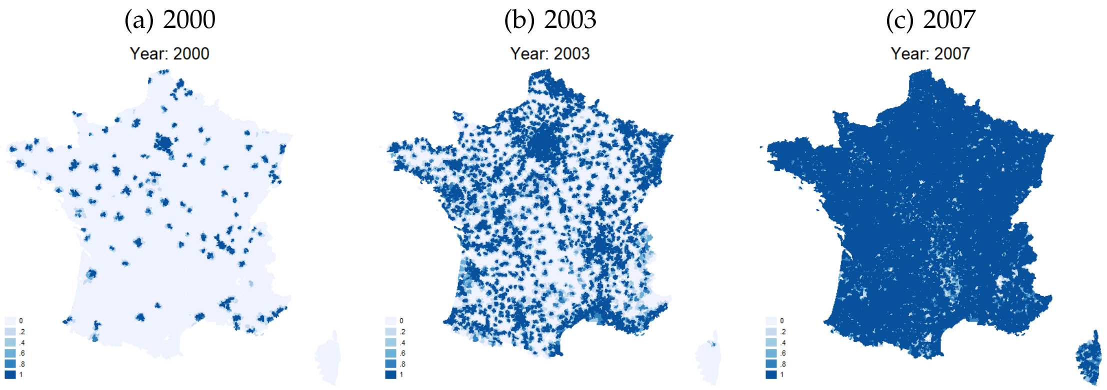
C ADSL in France

ADSL (Asymmetric Digital Subscriber Line) is a data communication technology that enables fast data transmission over copper telephone lines: bandwidth and bit rate are said to be asymmetric, meaning that they are greater towards the customer premises (downstream) than the reverse (upstream). Eligibility for ADSL depends on the distance between the final customer and a Local Exchange (LE), since the intensity and the quality of the analogue signal decreases as it is routed over the copper lines. LEs are telephone exchanges owned by the incumbent operator France Télécom into which subscribers' telephone lines connect. Initially dedicated to the telephone network, LEs are essential for internet users who subscribe to ADSL. LEs aggregate local traffic and then direct it via the so-called backbone (i.e. higher levels of the network) towards the World Wide Web. A key feature of ADSL technology is that one can supply high-speed internet by upgrading the LE while relying on the existing (copper) local loop to connect the premises of the final customers. The upgrading involves the installation of equipment inside the LE (a DSLAM) required in order to translate the analogical signal – transmitted via ADSL on the local copper loop – to a numerical signal that can be transmitted to the higher levels of the network. The upgrading of local LEs is the key source of variation that we use in our empirical analysis.

ADSL roll-out in France As evidenced by Malgouyres et al. (2021), the deployment of broadband internet technology beyond France's largest cities was slow at the beginning of the 2000's (see Table C1). The authors show that there were multiple reasons for this staggered deployment. First, France Télécom, the monopolistic telecom supplier, was uncertain regarding the future wholesale price it was going to be able to charge, mainly due to regulatory reasons. Second, at the same time that France Télécom had to invest massively in upgrading its LEs to ADSL, it went through a debt crisis that ended with what was essentially a government bailout in 2002. Urged on by the government – which increased its stake in the firm during the 2002 bailout of the firm – in 2003 France Télécom pledged to cover 90% of the French (mainland) population by the end of 2005, i.e. all LEs with more than 1,000 lines.

Between 2004 and 2007, local governments were involved in broadband internet deployment by subsidising the expansion and favouring competition among providers. Most relevant for broadband expansion was the creation of a contract between local governments, the Plan Département Innovant, whereby France Télécom pledged to equip all LEs in a département with more than 100 connections within a year. The proclaimed target of the plan was to raise coverage to 96% of the French population by the end of 2005 and activate all the remaining LEs by the end of 2006. We account for the role of local government in our empirical analysis by including département-year fixed effects. Overall, the account of the broadband expansion in France over the period suggests that it was gradual due to uncertainty regarding the capacity of France Télécom to undergo the investment until 2002. After 2002, with strong encouragement from the government, France Télécom started covering more secondary areas with a focus on the overall number of lines per LE, with only limited attention paid to local economic potential. Although the coverage was accelerated, it remained gradual due to France Télécom's operational limits and took about two years longer than anticipated in 2003. Because our main effects of interest are identified out of the gradual diffusion of the new technology in different LEs over space and time, addressing the endogeneity of the decision to "treat" one LE before another deserves special consideration. Malgouyres et al. (2021) show that broadband expansion occurred to maximise population coverage with no special consideration for economic potential, a fact that is strongly supported by the statistical analysis of the determinants of broadband coverage that they carried out.

FIGURE C1. The progressive roll-out of the DSL technology in France—$\widetilde{Z}$



Notes: This figure presents the geographical distribution of the continuous measure of local broadband availability (variable $\widetilde{Z}$).

Use of broadband technologies by firms ADSL technology, while progressively replaced by other technologies – notably direct access to the optic fibre or FTTO (fibre to the office) –, is the main way in which firms access the internet. A 2016 survey showed that in that year 73% of SMEs used ADSL technology (Arcep, 2016). The large take-up reflects the fact that ADSL was a massive improvement in terms of speed (from 56 to 512kbit/s for a transition from a classical to first generation ADSL connection) as well as in terms of connection cost and time. While there is no administrative data on firm-level use of broadband, based on repeated survey data, firms located in cities that received broadband internet earlier experienced higher growth in the proportion of employees that used internet on a regular basis between 1999 and 2004. This statistical association cannot be interpreted causally under the same set of assumptions as our main analysis. It is however strongly suggestive of an impact from broadband availability on broadband adoption.

D BI Expansion and Skill-Biased Technological Change

In this Appendix, we confirm and extend the results of Akerman et al. (2015) showing that broadband internet constitutes a skill-biased technology. In particular, we show that when a city is connected to BI (i) the labor productivity of establishments located in the city increases, (ii) the demand for high-skill workers increases, and (iii) the hourly wage and salary of high-skill workers increase.

D.1 At the city and establishment level

Our identification for the city level analysis follows a stacked difference-in-differences strategy, as reported in Equation 3. For the establishment level analysis, we follow the same model, but we include establishment fixed effects instead of city fixed effects. The results of the latter can be interpreted as the pure within-firm effect that excludes any changes due to composition. We start by evaluating the impact that BI and the underlying ADSL technology had on firm productivity. We measure labor productivity as the log of value added divided by the total wage. Given that the financial data is only available at the company level, we assign productivity to all the establishments of multi-plant firms according to one measured at the overall firm level. At the city level, we consider the average productivity obtained across the local establishments, weighted by their size.[44] Secondly - to capture skill-biased technological change - we look at the impact of BI on the share of high-skill workers within cities and establishments.[45]

Results obtained from both city and establishment-level regressions are reported in Figure D1 and the corresponding coefficients are given in Table D1. These findings confirm what was expected: the productivity of firms increases when the city in which they are located is connected to BI, whether measured by value adder per wagebill or using an estimate of the TFP.[46]. The average labor productivity of firms located in the city increases by about 1% over the first five years, and about half of this effect (0.6%)

[44] See Table I for summary statistics for the main outcome variables in the city level and establishment level samples.

[45] All our measures of employment are expressed in terms of full-time equivalents. High-skill workers are defined based on their occupation, and include executive positions, managers and engineers, which correspond to the highest socio-professional category.

[46] We construct the TFP at the aggregate firm level by following the method of Aghion et al. (2023) and then we assign it to establishments using employment weights.

takes place in firms already present in the area before the shock.[47]

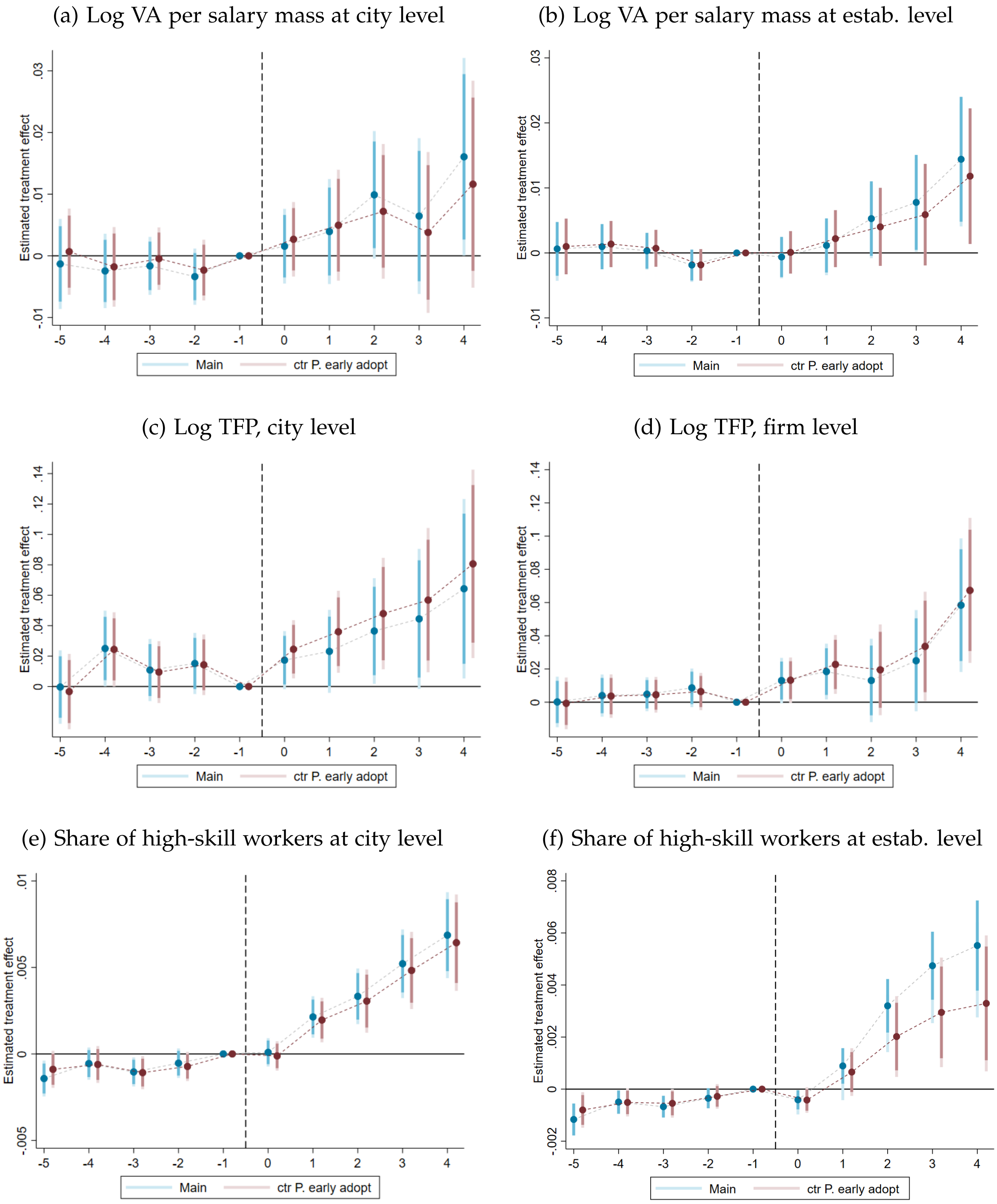
Similarly, before the arrival of BI, the share of high skill workers evolved comparably across cities belonging to different cohorts of ADSL diffusion, conditional on department-specific time trends and the other controls. When cities get access to BI, they experience a general upskilling of their labor force relative to other cities. In particular, the share of full-time employment accounted for by the top socio-professional category increases, which is in line with the thesis of skill biased technological change. In terms of magnitude, the share of high-skill workers in a city increases by 0.4 percentage points following the diffusion of BI. This effect can be compared with the baseline average observed in cities at the beginning of the period, which was 5.8%: the share of high-skill workers thus increases by about 6.9% after the arrival of BI with respect to the baseline.

Such results could arise for two reasons: either because BI fosters the entry of new establishments with a higher average skill level than the incumbents, or because the average establishment already present in the city increases its share of high-skill workers. To capture the extent to which composition effects play a role, we compare our city-level results with similar event studies at the establishment level, which only keep the plants already present in the city before the arrival of ADSL in the sample. The effect on high skill workers within existing establishments is qualitatively similar to the one at the city level. This suggests that the increase in share of skilled workers is not (only) driven by a composition effect but is also a phenomenon taking place within existing firms. The magnitude is however slightly smaller: BI increases the share of high skill workers within existing firms by 0.3 percentage points compared to a baseline average of 10% (3% growth with respect to baseline).

Figures D2 and D3 show the same robustness tests that we perform on the outsourcing outcomes. In Figure D2 we test that results hold when adding additional controls: i) pre-BI productivity growth in the city interacted with year dummies, ii) pre-BI sectoral composition in the city interacted with year dummies, iii) share of left-wing voters in the city in 1995 and an indicator of cities switching political majority between 1995 and 2002, both interacted with year dummies, iv) pre-BI city size, measured by the number of establishments in the city, interacted with year fixed effects, v) all the

[47] The positive effect of BI on labor productivity is not purely driven by an increase in the skill intensity of the firms located in the city, but goes beyond that. First, by dividing the value added of the firm by the wage bill, instead of the firm size, we partially account for the fact that high-skill workers are paid more. Second, if we include the share of high-skill workers as an additional control in the productivity regressions, the coefficients remain widely unchanged (results available upon request).

FIGURE D1. Firm productivity and broadband access



Notes: This Figure shows regression coefficients and 90% and 95% confidence intervals from a dynamic event study where the dependent variable is the log of value added per salary mass within a city or establishment (Panel a and b), TFP (Panel c and d) or the share of executive workers within a city of establishment (Panel e and f) at t and the specification follows equation 3. The blue lines present our baseline model, while the red lines present the model controlling for the propensity score of early adoption interacted with year fixed effects. We construct the TFP at the aggregate firm level by following the method of Aghion et al. (2023) and then we assign it to establishments using employment weights.

controls added together. Figure D3 shows the results obtained i) when controlling for the BI coverage of other cities in the same department - to get a sense of possible spill-

TABLE D1. Effect of ADSL on productivity and demand for high-skill workers

	(1)	(2)	(3)	(4)
	Sh. of high skill workers		Log VA / salary mass	
VARIABLES	City level	Estab. Level	City level	Estab. Level
T = 0	0.000653	-2.79e-05	0.00322	-0.000344
	(0.000477)	(0.000240)	(0.00330)	(0.00157)
T = +1	0.00269***	0.00125***	0.00563	0.00152
	(0.000663)	(0.000437)	(0.00452)	(0.00239)
T = +2	0.00386***	0.00352***	0.0115**	0.00565
	(0.000891)	(0.000653)	(0.00561)	(0.00348)
T = +3	0.00573***	0.00504***	0.00806	0.00815*
	(0.00109)	(0.000826)	(0.00669)	(0.00439)
T = +4	0.00738***	0.00583***	0.0177**	0.0148**
	(0.00134)	(0.00108)	(0.00861)	(0.00585)
Average effect	0.00406***	0.00312***	0.00924*	0.00596*
	(0.000822)	(0.000606)	(0.00538)	(0.00330)
Baseline mean	0.058	0.103	0.68	0.644
	(0.060)	(0.150)	(0.327)	(0.463)
Observations	423,770	3,075,954	416,052	2,911,303
R-squared	0.711	0.894	0.622	0.711

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. Columns (1) and (3) run the regression at the city level, following equation 3, where controls are the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level. Columns (2) to (4) run the same specification on the outcome computed at the establishment level, replacing city fixed effects by establishment fixed effects.

over effects of BI arrival on control cities - , ii) when controlling for fixed effects at the commuting zone × year level instead of department × year, iii) when introducing the continuous measure of treatment $\tilde{Z}_{it}$ instead of the binary treatment, iv) when running a standard dynamic two-way fixed effects model as reported in equation (2). Figure D4 shows the placebo tests consisting in splitting late receivers into two groups according to their propensity of early adoption, and evaluating the pseudo-treatment on the period preceding their actual BI connection. The graphs mostly show flat and non-significant differences across the two groups, and if anything trends in the opposite direction than our actual results, which comfort our assumption that probability of early adoption is all but inflating our main coefficients. Table D3 shows the static coefficients obtained from a stacked difference-in-differences on the post-BI period, and Table D4 shows the coefficients from a standard staggered regression run at the labor market area (*Zone d'emploi*) level where the post BI dummies are interacted with the continuous measure of BI coverage in the area. Once again, most of the outcomes remain unchanged, except for outsourcing expenditure that becomes flat in the standard staggered event study model.

D.2 At the individual level

In this subsection, we show that the evidence of increasing demand for skilled workers translates into increased wages, for our individual panel. As explained in Section 3, our data allow us to follow part of the workers over time. More precisely, we can follow every worker born in October of an even year (roughly 1/24 of the population) between 1994 and 2010. With these data, we can look at the individual wage effect of BI expansion, i.e., we can consider the change in hourly wage that follows the connection of a worker's city to ADSL. We therefore estimate the following model:

$$\log(w_{i,t}) = \beta \tilde{Z}_{c(i),t} + X\gamma + \psi_{d,t} + \nu_i + \zeta_{s(i)} + \varepsilon_{i,t}, \tag{6}$$

where $w_{i,t}$ is the hourly wage of individual i over year t on average. $\tilde{Z}_{c(i),t}$ is the variable that captures the share of the city $c(i)$, where individual i works, that is connected to BI. To some reasonable extent, $\tilde{Z}$ can be seen as a dummy variable indicating whether the city has been connected to BI prior to year t. X is a vector of time-varying individual characteristics: age, age squared, and an indicator of whether the job is part-time (as opposed to full-time). Finally, $\psi_{d,t}$, ν_i, $\zeta_{s(i)}$ are a set of department d times year t fixed effects, individual fixed effects and sector $s(i)$ fixed effects. ε is an idiosyncratic error that we assume can be correlated within departments but not across. Finally, β captures the effect (in percentage points) of being connected to BI on wage, controlling for observable and time-unvarying unobservable worker characteristics.

Table D2 presents our results and Table D5 presents the summary statistics of the variables used for the regression. Column (1) includes all workers (around 8 millions) and shows that the coefficient of the dummy variable $C_{c(i),t}$ (first line, labeled "connected") is positive and significant. Its magnitude suggests that the hourly wage permanently increases by 3% on average for all workers once connected to BI. In this specification, we did not include individual fixed effects ν_i but control for initial wage

TABLE D2. Effect of ADSL on individual wage

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All workers		3 skills		2 skills	
Connected	0.030***	0.006***	0.013***	-0.016***	0.010*	-0.014***
	(0.003)	(0.001)	(0.004)	(0.003)	(0.005)	(0.003)
× High-Skilled			0.042***	0.116***	0.052***	0.116***
			(0.013)	(0.007)	(0.015)	(0.009)
× Int-Skilled			0.004	0.025***		
			(0.004)	(0.003)		
Age	0.032***	0.044***	0.026***	0.041***	0.020***	0.035***
	(0.003)	(0.006)	(0.002)	(0.005)	(0.001)	(0.003)
Age Sq.	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	0.106***		0.123***		0.125***	
	(0.004)		(0.007)		(0.002)	
Short Time	-0.043***	0.035***	-0.020***	0.035***	0.001	0.059***
	(0.009)	(0.001)	(0.004)	(0.001)	(0.005)	(0.002)
High Skill			0.649***	0.210***	0.644***	0.337**
			(0.005)	(0.005)	(0.008)	(0.007)
Int. skill			0.168***	0.039***		
			(0.003)	(0.002)		
Initial wage (log)	0.346***		0.334***		0.249***	
	(0.025)		(0.016)		(0.020)	
Fixed Effects						
LMA × year	✓	✓	✓	✓	✓	✓
Sector	✓	✓	✓	✓	✓	✓
Individual		✓		✓		✓
Obs.	7,810,286	7,808,176	7,810,286	7,808,176	4,316,357	4,256,281
R Sq.	0.46	0.78	0.62	0.79	0.70	0.85

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. This Table shows regression results from an estimation of equation (6). Variable description is given in Table D5 of the Online Appendix A. All workers are included in the regressions, except in column (5) and (6) in which we drop intermediate skill workers. All regressions include a département times year fixed effect as well as a sector fixed effect at the 2 digit level. Columns (2), (4) and (6) also include an individual fixed effect. Heteroskedasticity robust standard errors clustered at the département level under parenthesis.

to capture the level of skill of the worker.[48] Including an individual fixed effect would better control for unobserved worker heterogeneity (which includes education) and this is presented in column (2). Our coefficient of interest remains positive and significant but somehow lower (0.6%). Columns (3) and (4) produce the same type of regression as Akerman et al. (2015) where we interact $C_{c(i),t}$ with a dummy variable for each skill level. In line with their results, we see that the effect of BI on wages is significantly larger for high skill-workers than for others. Columns (5) and (6) confirm these results by restricting our analysis to only low and high-skill workers (i.e. excluding intermediate skill workers from the sample).

[48]Initial wage is defined as the logarithm of wage per hour taken in the first year in which the worker appears in the panel, this year is then removed from the regression.

Overall, these results confirm what we reported at the city level: BI is associated with a larger demand for high-skill workers and this translates into higher wages, even when controlling for unobserved heterogeneity and the usual controls. These results also show that the increasing demand for high-skill workers observed at the city and establishment level is not a pure composition effect as, overall, the arrival of BI benefits this class of workers more.

D.3 Additional Tables and Figures

TABLE D3. Effect of ADSL on skill-biased technical change - static regressions

	Log VA / salary mass	Sh. of high skill workers
Panel A : city level regressions		
Post ADSL * treated	0.00550	0.00204***
	(0.00393)	(0.000571)
Observations	416,052	423,770
R-squared	0.622	0.711
Panel B : establishment level regressions		
Post ADSL * treated	0.000925	0.000942***
	(0.00188)	(0.000334)
Observations	2,911,303	3,075,954
R-squared	0.711	0.894

Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. The regressions are run at the city and establishment level following a model similar to equation 3, but where instead of including the dynamic post-ADSL effects for every year, we just include a dummy for post-ADSL period interacted with the treatment indicator. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects.

TABLE D4. Effect of ADSL on skill-biased technical change - regressions at labor market area level

	(1) Sh. of high skill workers	(2) Log VA / salary mass
T = 0 x Zemp coverage	0.000876	0.0656
	(0.00244)	(0.0574)
T = +1 x Zemp coverage	0.00453***	0.0706
	(0.00136)	(0.0512)
T = +2 x Zemp coverage	0.0104***	0.0935*
	(0.00171)	(0.0512)
T = +3 x Zemp coverage	0.0156***	0.115
	(0.00217)	(0.0716)
T = +4 x Zemp coverage	0.0206***	0.136
	(0.00286)	(0.0944)
Average effect	0.0104***	0.0960*
	(0.00172)	(0.0563)
Observations	2,783	2,783
R-squared	0.989	0.781

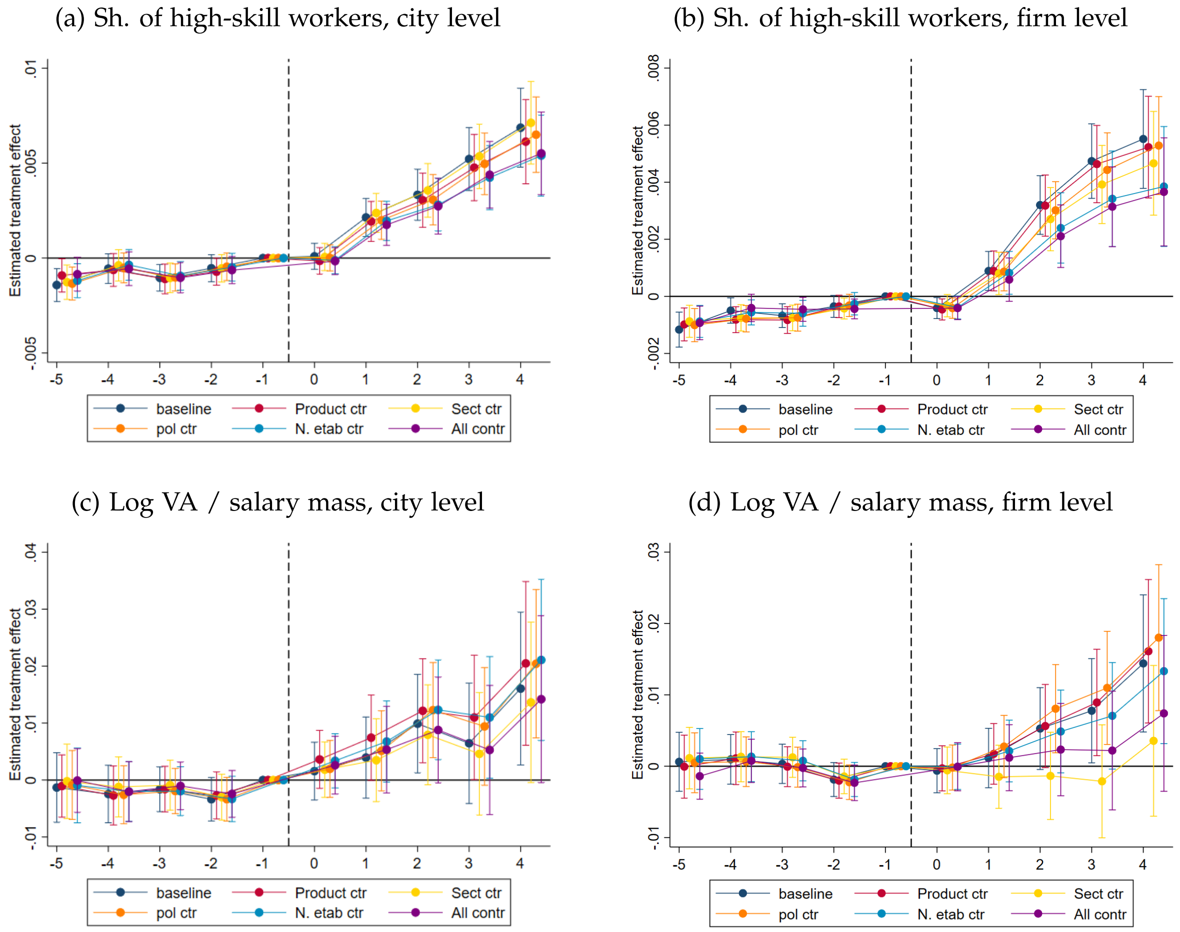
Notes: ***, ** and * respectively denote significance at the 1, 5 and 10% level. The regressions are run at the labor market area (*Zone d'emploi*) level. Given that there is little variation in the timing of first BI appearance in labor market areas within the same department, we take advantage of the continuous measure of BI coverage: we estimate a standard staggered model similar to equation 2, but where we interact the dynamic post-BI dummies for every year with the share of the labor market area that is covered in that period. All columns control for the population density in 1999 interacted with year dummies, department × year fixed effects, and labor market area fixed effects.

TABLE D5. Variable description for Table D2

Variable	Description	Mean	p25	p75
Log of wage	log of hourly wage (dependent variable)	2.41	2.10	2.63
Age	Age of the worker	37	28	46
Age Sq.	Age × Age	1,507	784	2,116
Gender	Gender of the worker	0.63	0	1
Short Time	Dummy for declaring working part time	0.17	0	1
High Skill	Dummy for working in a high skill occupation	0.13	0	1
Int. Skill	Dummy for neither working in high or low skill occupation	0.45	0	1
Initial Wage (log)	Log of hourly wage taken in the first year the worker appear in the data	2.22	1.93	2.40

Notes: Variable description used in the panel data wage regression and basic descriptive statistics.

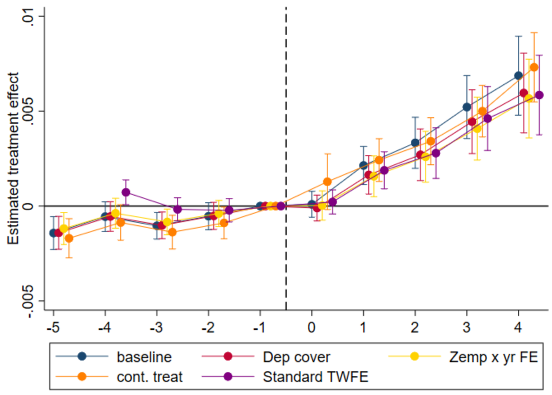
FIGURE D2. Robustness tests on SBTC outcomes: adding additional controls



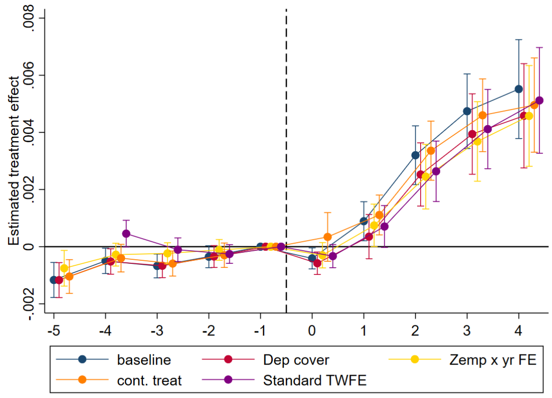
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating equation (3) on city- and firm-level data with different sets of controls. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects or firm fixed effects depending on the level of aggregation, and sample fixed effects. Standard errors are clustered at the department level. The navy blue line shows the baseline model that we use in the main analysis for comparison. The red line adds controls for the productivity growth observed in each city between 1996 and 1998, interacted with year dummies. The yellow line adds controls for the sectoral composition in each city prior to 1999 interacted with year fixed effects. The orange line adds controls for the share of left-wing votes in the presidential election of 1995 interacted with year dummies and a dummy for wether there was a change in majority between 1995 and 2002, also interacted with year dummies. The light blue line controls for city size prior to 1999, measured as the number of establishments active in the city, interacted with year fixed effects. Finally, the purple line adds all the controls at once.

FIGURE D3. Robustness tests on SBTC outcomes: other robustness tests

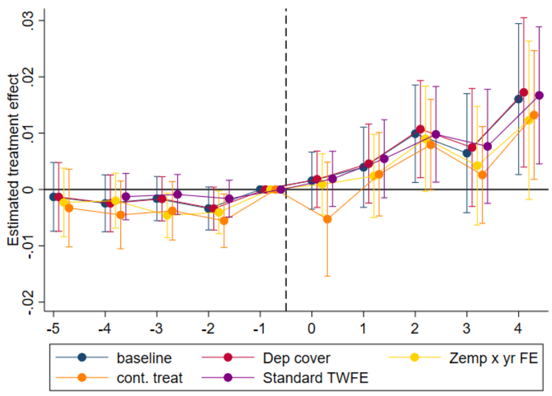
(a) Sh. of high-skill workers, city level



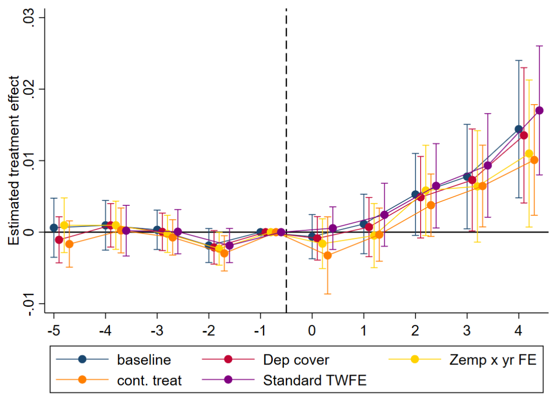
(b) Sh. of high-skill workers, firm level



(c) Log VA / salary mass, city level



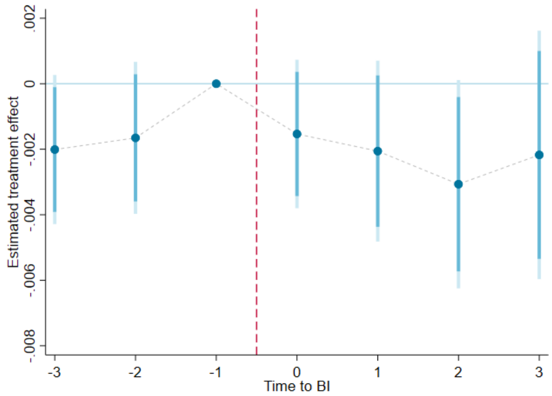
(d) Log VA / salary mass, firm level



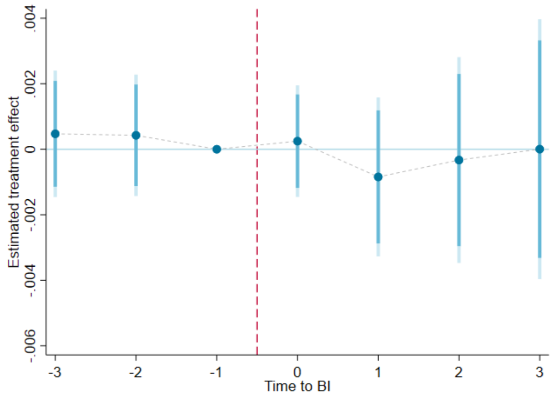
Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from estimating slightly different models. All models control for the population density in 1999 interacted with year dummies, department $\times$ year fixed effects, city fixed effects or firm fixed effects depending on the level of aggregation, and sample fixed effects. Standard errors are clustered at the department level. The blue line shows the baseline model that we use in the main analysis for comparison. The red line adds a control for the BI coverage observed in the other cities within the same department. The yellow line shows the results obtained from running a standard staggered difference-in-differences model as in equation 2. Finally, the orange line, which is only present for the outsourcing expenditure outcome, tests the robustness of this outcome from excluding multi-establishment firms, for which we cannot properly allocate performance across plants.

FIGURE D4. Robustness tests on SBTC outcomes: Placebo tests

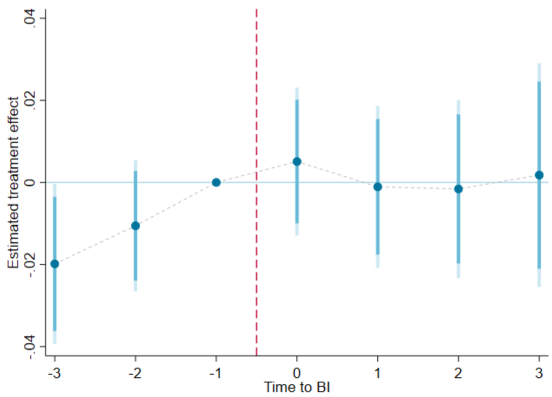
(a) Sh. of high-skill workers, city level



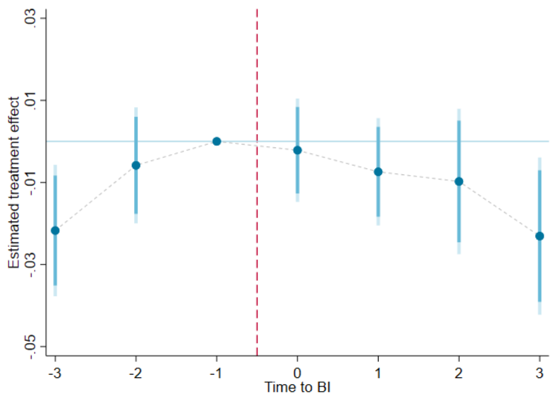
(b) Sh. of high-skill workers, firm level



(c) Log VA / salary mass, city level



(d) Log VA / salary mass, firm level



Notes: This Figure shows the point-estimate and 90% confidence intervals of the event study obtained from placebo regressions. All models control for the population density in 1999 interacted with year dummies, department × year fixed effects, city fixed effects and sample fixed effects. Standard errors are clustered at the department level. Late receivers of broadband (2004 to 2007) are split into high (HPLR) and low propensity (LPLR) to be early receivers based on the propensity score. The HPLR are assigned to the pseudo-treatment year computed as the actual year of treatment - 4. The graph presents the pseudo-treatment effect observed over the period where none of the cities in the sample is actually treated (1997 to 2003).

E A simple illustrative model

In this Appendix, we show how a simple model can generate the prediction that a global shock such as BI, which affect firms productivity and outsourcing cost, can lead firms to increase their outsourcing of some specific occupations.

Production technology: aggregation across occupations. Firms combine several occupations or tasks to produce output using a Cobb-Douglas function with constant returns to scale.[49] We denote output of j as a function of each occupation output $H_{i,j}$ as:

$$Y_j = \theta_j \prod_{i \in \mathbf{N}} H_{i,j}^{\alpha_i} \tag{7}$$

where θ denotes a Hicks neutral productivity shifter, $\mathbf{N}$ is the set of occupations and we have $\sum_i \alpha_i = 1$, and $\alpha_i \in [0,1]$.

Production technology: in-house and outsourced workers within occupation. Each occupation i can be carried out by a mix of in-house workers which are directly employed and of outsourced workers whose labor services are hired through a third party (subcontractor). Each occupation is characterized by a specific elasticity of substitution between in-house and outsourced workers. Output by occupation i depends on the number of in-house and outsourced workers denoted n_i and s_i respectively, and is expressed as:[50]

$$H_i = \left(\mu_i^{\frac{1}{\sigma_i}} n_i^{\frac{\sigma_i - 1}{\sigma_i}} + (1 - \mu_i)^{\frac{1}{\sigma_i}} s_i^{\frac{\sigma_i - 1}{\sigma_i}} \right)^{\frac{\sigma_i}{\sigma_i - 1}} \tag{8}$$

where σ_i is the elasticity of substitution between the services provided by in-house and outsourced workers and μ_i affects the relative productivity of the groups. A *core occupation* is defined as an occupation with a low elasticity of value for σ_i. It could be either a high or a low productivity occupation as measured by α_i, i.e. the elasticity of overall output Y to the occupational output H_i.

[49] As in the empirical analysis, we make the assumption that one occupation is a fixed bundle of tasks.

[50] To be more consistent with the empirical analysis, we adopt an "occupation" approach. We can see each occupation as a continuum of tasks, some of which will be performed by outsourced workers and other by in-house workers. At the equilibrium, an occupation is therefore characterized by its relative level of outsourced workers, which in turns is determined by the elasticity of substitution σ_i.

The model encapsulates the idea outlined in Section 2 that firms differentiate occupations based on how core they are. This is captures by the parameter σ_i. The elasticity of substitution σ_i will determine the extent to which firms wish to increase outsourcing as the relative cost of doing so goes down. A core occupation in that set-up is a bundle of tasks that is hard to codify and therefore has a low σ_i, which in turn implies that a decline in the cost of outsourcing will not provide a strong incentive to outsource this task. The economic value produced by the task is captured by its weight in the Cobb-Douglas aggregation (α_i). A core task with high economic potential is therefore an occupation with a high α_i and a low σ_i. On the contrary, a non-core task is characterized by a low α_i and a high σ_i. As we will see below, in the model, profit maximization implies that a decline in the relative cost of outsourcing, or an increase in the optimal scale of the firm, will lead to a refocusing of the firm on core tasks. As a consequence, the share of core occupations in the overall wage bill increases.

(Labor) market structure for in-house and outsourced workers. A key difference between the hiring of in-house and outsourced workers is that each firm disposes of some wage setting power when hiring in-house workers but are price-takers with respect to the firms from which they outsource (which we call the agencies). We micro-found (occupation-specific) firm-level labor supply curves as resulting from a discrete choice modeling and in keeping with the recent literature on monopsony (Card et al., 2018; Lamadon et al., 2019). In this set-up, the labor supply curve that individual firms face (within a given occupation) is not perfectly elastic because of idiosyncratic tastes among workers for the amenities offered by the firms (for instance working conditions, commute, corporate culture). Due to asymmetric information regarding the valuation by individual workers of such amenities, firms are not able to perfectly discriminate and fully price these amenities into individual-specific wages. As we will see this assumption naturally generates the positive correlation between outsourcing intensity and size which showed in Figure I that is key in this model.[51]

This idea is summarized by equation (9) which gives the labor supply curve of a firm j hiring a (in-house) worker in occupation i. Namely:

[51] We assume the market for outsourcing services is competitive and that consequently there is not rent-sharing between employers and their outsourced workers. This does not preclude the possibility that outsourced workers benefits from rent-sharing with respect to their direct employer (the agencies) due to frictions on the labor market.

$$n_{i,j} = N_i \frac{w_{i,j}^{1/\rho_i}}{\sum_j w_{i,j}^{1/\rho_i}} = a_i w_{i,j}^{\frac{1}{\rho_i}}, \tag{9}$$

where N_i is the measure of the population of workers in occupation i with iid extreme value type-1 preferences across firms with shape parameters ρ_i.[52] We consider a standard atomistic monopsonistic competition setting as firms ignore their own impact on the competition index which is captured by a_i. For simplicity, we consider in our model that all occupations i have the same value of $\rho_i > 0$ and a_i which we denote as ρ and a.

Profit maximization. We consider a set-up with monopolistic competition and CES demand. Each firm j faces the demand function $Y^D = p^{-\varepsilon} I$ which yields the following revenue function:

$$R(Y) = Yp = Y^{\frac{\varepsilon-1}{\varepsilon}} I^{\frac{1}{\varepsilon}} \tag{10}$$

The cost associated with hiring a vector of workers $\{n_{i,j}, s_{i,j}\}_{i\in\mathbf{N}}$ writes as :

$$C(\{n_i, s_i\}_{i\in\mathbf{N}}) = \sum_{i\in\mathbf{N}} n_{i,j} w_i(n_{i,j}) + \sum_{i\in\mathbf{N}} s_{i,j} \cdot \gamma_{i,j} r_i \tag{11}$$

where $w_i(n_{i,j})$ is the inverse labor supply function faced by firm j when hiring in occupation i. The variable r_i is the market price for outsourcing services in occupation i and $\gamma_{i,j}$ is the firm-specific cost shifter of outsourcing.

$$\max_{\{n_{i,j}, s_{i,j}\}_{i\in\mathbf{N}}} \pi_{i,j} = Y(\{n_{i,j}, s_{i,j}\}_{i\in\mathbf{N}})^{\frac{\varepsilon-1}{\varepsilon}} I^{\frac{1}{\varepsilon}} - \left(\sum_{i\in\mathbf{N}} n_{i,j} w_i(n_{i,j}) + \sum_{i\in\mathbf{N}} s_{i,j} \cdot \gamma_{i,j} r_i \right) \tag{12}$$

It is fairly straightforward to show that the problem defined in Equation (12) admits a unique positive solution $\{n^*_{i,j}, s^*_{i,j}\}_{i\in\mathbf{N}}$.[53]

Unlike what would occur under a competitive labor market, occupation-firm specific optimal wage $w^*_{i,j}$ depend on the level of labor demand $n^*_{i,j}$. This dependence precludes any closed form solution for $n^*_{i,j}$ but under some conditions on ρ allows us to

[52] This labor supply function arises from worker k in occupation i having utility: $u_{i,j,k} = w_{i,j} + e_{i,j,k}$, where $e_{i,j,k}$ follows an extreme-value type I distribution with scale parameters ρ_i.

[53] The problem with fixed wages $w_{i,j}$ is entirely standard and $\pi_{i,j}$ is strictly concave in $\{n_{i,j}, s_{i,j}\}$ so that any first order condition correspond to a global maximum. Allowing $w_{i,j}$ to increase with respect to $n_{i,j}$ make the profit function more concave and does not alter the uniqueness and existence of the solution.

derive our main predictions.

E.1 Predictions from the model

Without lost of generality, we consider that:

$$1 \leq \sigma_1 < \sigma_2 < \ldots < \sigma_N.$$

The first-order conditions with respect to s_i and n_i for all occupations $i \in \mathbf{N}$ leads to the following relationship:

$$s_{i,j} = \lambda_{i,j} n_{i,j}^{\rho\sigma_i+1}, \text{ where } \lambda_{i,j} = \frac{1-\mu_i}{\mu_i}\left[\frac{\rho+1}{a_i^{\rho} r_i \gamma_{i,j}}\right]^{\sigma_i}. \tag{13}$$

Because of this relationship, a firm can only increase its size by increasing its number of in-house workers as well as its outsourcing expenditures. $\lambda_{i,j}$ is a coefficient that measure the relative cost of these two types of labor and the level of complementarity. We assume that the parameters are distributed such that:

$$\lambda_{1,j} < \lambda_{2,j} < ... < \lambda_{N,j}.$$

We keep the setup as simple as possible and assume that there are only two types of occupations 1 and 2. Occupation 1 is the "core" occupation which is associated with a value of $\sigma_1 = 1$ and a value $\alpha_1 > 1/2$. By contrast, occupation 2 is the "non-core" occupation where in-house workers are more easily substituable by outsourcing workers ($\sigma_2 > 1$). We primarily present results pertaining to an increase in productivity. We also present a numerical resolution of the model.

Proposition 1. *A positive increase in θ raises the cost share of outsourcing for each occupation i for which $\sigma_i > 1$*

Proof. Note: we drop the index j when the context does not command it.

First, the CES structure of the production function for a given occupation yields the following elasticities:

$$
\begin{aligned}
\frac{\partial H_i}{\partial n_i} &= H_i^{1/\sigma_i}\mu_i^{1/\sigma_i}n_i^{-1/\sigma_i} \Longrightarrow \frac{\partial H_i}{\partial n_i}\frac{n_i}{H_i} = H_i^{\frac{1-\sigma_i}{\sigma_i}}\mu_i^{\frac{1}{\sigma_i}}n_i^{\frac{\sigma_i-1}{\sigma_i}} \\
\frac{\partial H_{i,j}}{\partial s_{i,j}} &= H_{i,j}^{1/\sigma_i}(1-\mu_i)^{1/\sigma_i}s_{i,j}^{-1/\sigma_i} \Longrightarrow \frac{\partial H_i}{\partial s_i}\frac{s_i}{H_i} = H_i^{\frac{1-\sigma_i}{\sigma_i}}(1-\mu_i)^{\frac{1}{\sigma_i}}s_i^{\frac{\sigma_i-1}{\sigma_i}}
\end{aligned}
$$

Note also that this elasticity:

$$
e_i \equiv \frac{\partial H_i}{\partial s_i}\frac{s_i}{H_i} = \frac{(1-\mu_i)^{\frac{1}{\sigma_i}}s_i^{\frac{\sigma_i-1}{\sigma_i}}}{(1-\mu_i)^{\frac{1}{\sigma_i}}s_i^{\frac{\sigma_i-1}{\sigma_i}}+\mu_i^{\frac{1}{\sigma_i}}n_i^{\frac{\sigma_i-1}{\sigma_i}}} \in [0,1]
$$

and $\frac{\partial H_i}{\partial n_i}\frac{n_i}{H_i} = 1-e_i$.

Second, the first-order conditions can be combined to give a relationship between s_i and n_i:

$$
s_i = \frac{1-\mu_i}{\mu_i}\left[\frac{\rho+1}{a_i^{\rho}r_i\gamma_i}\right]^{\sigma_i} n_i^{\rho\sigma_i+1} = \lambda_i n_i^{\rho\sigma_i+1},
$$

and the cost share of outsourced workers is thus given by:

$$
\eta_i^c \equiv \frac{\gamma_i r_i s_i}{\gamma_{i,j} r_i s_i + w(n_i)n_i} = 1 - \frac{1}{1+\gamma_i r_i a^{\rho}\lambda_i n_i^{\rho(\sigma_i-1)}}.
$$

As long as $\sigma_i > 1$ and $\rho > 0$, we therefore have:

$$
\frac{\partial \eta_i^c}{\partial n_i} > 0.
$$

Using the relationship between n_i and s_i and log differentiating H_i, it is straightforward to show that

$$
d\log(H_i) = d\log n_i\left(1+H_i^{1/\sigma_i-1}(1-\mu_i)^{1/\sigma_i}s_i^{1-1/\sigma_i}\rho\sigma_i\right) = d\log n_i\,(1+e_i\rho\sigma_i)
$$

Next, log-differentiating PY:

$$
d\log\theta\frac{\varepsilon-1}{\varepsilon} + \left(\sum_{i'}\alpha_{i'}d\log(H_{i'})\right)\frac{\varepsilon-1}{\varepsilon} = (1/\sigma_i+\rho)\,d\log n_i + d\log H_i,
$$

which can be rewritten as:

$$d\log\theta + \left(\sum_{i'}\alpha_{i'} d\log n_{i'}(1+e_{i'}\rho\sigma_{i'})\right) = \frac{\varepsilon}{\varepsilon-1}\left(1/\sigma_i + \rho + 1 + e_i\rho\sigma_i\right) d\log n_i. \quad (14)$$

This expression is valid for all i which shows that $d\log n_i$ are either all positive or all negative as $d\log\theta > 0$. To show that they are all positive, we first multiply the above equation by α_i and then sum for all i:

$$d\log\theta = \frac{1}{\varepsilon-1}\left(\sum_{i'}\alpha_{i'} d\log n_{i'}(1+e_{i'}\rho\sigma_{i'} + \varepsilon(1/\sigma_{i'}+\rho))\right) > 0.$$

This implies that $\frac{d\log(n_i)}{d\log\theta} > 0$ and then $\frac{d\eta_i^c}{d\theta} > 0$. □

The intuition for this result comes from the fact that firms respond to a positive productivity shock by increasing their workforce. As long as the elasticity of substitution between the two types of workers is larger than 1, then the firm will adjust both its number of in-house and outsourced workers. Yet, because $\rho > 0$, as the firm grows, it is more and more costly to hire in-house workers and the ratio η_c of the labor cost coming from outsourcing over the total labor force increases.

Proposition 2. *Following an increase in θ, the increase in the cost share of outsourcing is larger for the non-core occupations*

Proof. Starting from equation (14) and using the fact that $s_i = \lambda_i n_i^{\rho\sigma_i+1}$, we know that:

$$\frac{1}{(\rho\sigma_i+1)}\frac{d\log(s_i)}{d\log(\theta)}\left(\frac{1}{\sigma_i} + 1 + \rho + \rho\sigma_i e_i\right),$$

is independent of i. Hence, a sufficient condition to have $\frac{d\log(s_1)}{d\log(\theta)} < \frac{d\log(s_2)}{d\log(\theta)}$ is:

$$(\rho\sigma_2+1)\left(\frac{1}{\sigma_1} + 1 + \rho + \rho\sigma_1 e_1\right) = (1+\rho\sigma_2)(2+\rho+\rho e_1) > (\rho+1)\left(\frac{1}{\sigma_2} + 1 + \rho + \rho\sigma_2 e_2\right)$$

Because $e_1 \in (0,1)$, then a larger sufficient condition is:

$$(1+\rho\sigma_2)(2+\rho) > (1+\rho)\rho\sigma_2 + (1+\rho)(1+\frac{1}{\sigma_2}+\rho)$$

which is true as long as $\sigma_2 > 1+\rho$.

Similarly, equation (14) can be used to show that:

$$\frac{d\log(n_i)}{d\log(\theta)}\left(\frac{1}{\sigma_i}+1+\rho+\rho\sigma_i e_i\right),$$

is independent of i. This shows that as long as:

$$\sigma_2 e_2 > \frac{1+\rho}{\rho}, \text{ then } \frac{d\log(n_2)}{d\log(\theta)} < \frac{d\log(n_1)}{d\log(\theta)}.$$

This show that:

$$\frac{d\log(s_1/n_1)}{d\log(\theta)} < \frac{d\log(s_2/n_2)}{d\log(\theta)},$$

and thus:

$$\frac{d\log(r_1\gamma_1 s_1/(n_1 w(n_1))}{d\log(\theta)} < \frac{dlog(r_2\gamma_2 s_2/(n_2 w(n_2))}{d\log(\theta)}.$$

Then following an increase in θ, the non-core occupation will experience a relative increase in the share of its labor cost coming from outsourced workers that is larger than what the core occupation experiences. In fact, because we have assumed that $\sigma_1 = 1$, the core occupation do not experience any change in its cost share of outsourced workers which concludes the proof. □

This Proposition shows that all occupations will not be affected equally by the BI shock. The high σ_i (non-core) occupations will become increasingly composed of outsourced workers. While we cannot directly identify these occupations, in the empirical part of the paper we show that workers are more likely to move to a service firm specialized in tasks that are typically considered as non-core (cleaning services, driving, security...) following the BI shock.

Proposition 3. *Following an increase in θ, the concentration of in-house workers increases within firms.*

Proof. The first order conditions can be combined to show that:

$$\frac{n_i w_i}{PY} = \alpha_i \frac{\varepsilon-1}{\varepsilon}\frac{1-e_i}{1+\rho} \text{ and } \frac{r_i s_i}{PY} = \alpha_i \frac{\varepsilon-1}{\varepsilon} e_i$$

so that the revenue share of occupation i is given by:

$$\frac{n_i w_i + r_i s_i}{PY} = \alpha_i \frac{\varepsilon-1}{\varepsilon}\frac{1+\rho e_i}{1+\rho} \in \left[\alpha_i \frac{\varepsilon-1}{\varepsilon(1+\rho)}; \alpha_i \frac{\varepsilon-1}{\varepsilon}\right]$$

This shows that as long as $\alpha_{i+1} < \frac{\alpha_i}{1+\rho}$, the revenue share increases as σ_i decreases. Note that with two occupations 1 and 2, this is true as long as:

$$\rho < \frac{2\alpha_1 - 1}{1 - \alpha_1}$$

Because $\lambda_1 < \lambda_2 < \ldots < \lambda_N$, then:[54]

$$n_i w_i + r_i s_i > n_{i+1} w_{i+1} + r_{i+1} s_{i+1} \implies n_i > n_{i+1}$$

Adding to the fact that $\frac{d\log(n_1)}{d\log(\theta)} > \frac{d\log(n_2)}{d\log(\theta)}$, this shows that the larger occupation in terms of in-house workers ($n_1 > n_2$) is also the one that will increase the most its number of in-house workers, which results in an increase in the HHI index. $\square$

Proposition 3 is easy to look at in the data as we directly observe in-house occupation composition (while we do not have direct measure of outsourcing expenditures by occupation). This result predicts that when a firm is connected to BI, its HHI of concentration should increase.

In this baseline version of the model, there are only two types of occupations. We did this to keep the model as simple as possible while keeping the core economic intuition. In Appendix E.3, we provide a numerical illustration of the comparative statics of the model. We solve the profit maximization problem of the firm for a specific case (with 4 occupations) and show how the optimal choices vary as productivity increases and the cost of outsourcing decreases. Results from this simple exercise show that outsourcing intensity increases with size (as measured by sales) and that a positive productivity shock or a decline in outsourcing cost is associated with rising HHI.

E.2 The case of a reduction in the cost of outsourcing

So far we have considered the effect of an increase in θ. As we have explained in Section 2, BI is also likely to have reduced the cost of outsourcing for firms. In this extension, we consider the case of a reduction in the value of $\gamma_{i,j}$ for a firm j. We assume that the relative decrease is the same for all occupations, i.e. that $d\log(\gamma_{i,j}) = d\log(\gamma)$. As usual, we drop the subscript j for the sake of clarity.

[54] This is because $n_{i+1} w_{i+1} + r_{i+1} s_{i+1} = a^{-\rho} n_{i+1}^{\rho+1} + \lambda_{i+1} n_{i+1}^{\rho\sigma_{i+1}+1} > a^{-\rho} n_{i+1}^{\rho+1} + \lambda_i n_{i+1}^{\rho\sigma_i+1}$

We show that under a large set of assumptions, firms respond to a reduction of the cost of outsourcing γ by increasing their outsourcing intensity which results in an increasing level of concentration of occupation in the firm.

To show this, first note that as long as $\sigma_i > 0$:

$$\frac{d\log(\eta_i^c)}{d\log(\gamma)} < 0 \Longleftrightarrow \frac{d\log(n_i)}{d\log(\gamma)} < 1/\rho$$

The combination of the two first order conditions continue to give the same relationship between n_i and s_i, only this time:

$$d\log(s_i) = -\sigma_i d\log(\gamma) + (\rho\sigma_i + 1)d\log(n_i) \tag{15}$$

Lemma 1. *At least one type of occupation must have $d\log(s_i)/d\log(\gamma) < 0$*

Proof. The full differentiation of $d\log(H_i)$ gives:

$$d\log(H_i) = e_i d\log(s_i) + (1-e_i)d\log(n_i) = d\log(s_i)\frac{1+\rho\sigma_i e_i}{1+\rho\sigma_i} + \frac{(1-e_i)\sigma_i}{1+\rho\sigma_i}d\log(\gamma)$$

Hence, differentiating the first order condition with respect to s_i and summing over all i after having pre-multiplied by α_i

$$\frac{\varepsilon-1}{\varepsilon}\sum_{j\in\mathbf{N}}\alpha_j d\log(H_j) = d\log(H_i) + d\log(\gamma) + \frac{1}{\sigma_i}d\log(s_i),$$

becomes:

$$-\sum_{i\in\mathbf{N}}\alpha_i\frac{d\log(s_i)}{d\log(\gamma)}\left[\frac{1}{\varepsilon}\frac{1+\rho e_i\sigma_i}{1+\rho\sigma_i} + \frac{1}{\sigma_i}\right] = 1 + \frac{1}{\varepsilon}\sum_{i\in\mathbf{N}}\alpha_i\frac{1-e_i}{1+\rho\sigma_i}\sigma_i > 0.$$

Which shows that at least one $\frac{d\log(s_i)}{d\log(\gamma)}$ must be smaller than 0.

$\square$

Coming back to the two type of occupation case where $\mathbf{N} = \{1, 2\}$ and $\sigma_1 = 1$, we know that η_1^c is constant and η_2^c will increase following a drop in γ if $d\log(n_2)/d\log(\gamma) < 1/\rho$. Let's assume that this is not the case, i.e. that $d\log(n_2)/d\log(\gamma) \geq 1/\rho > 0$.

Then $d\log(s_2)/d\log(\gamma) > 1/\rho$ from equation (15). And from the previous lemma, we know that $d\log(s_1)/d\log(\gamma) < 0$.

Using again equation (15), we also have

$$\frac{d\log(n_1)}{d\log(\gamma)} < \frac{\sigma_1}{\rho\sigma_1 + 1} \le \frac{1}{\rho},$$

and finally:

$$\frac{d\log(H_1)}{d\log(\gamma)} < \frac{1-e_1}{\rho} < \frac{1}{\rho} \text{ while } \frac{d\log(H_2)}{d\log(\gamma)} > \frac{1}{\rho}$$

Using the differentiated first order condition with respect to the second occupation yields:

$$\frac{\varepsilon-1}{\varepsilon}\left(\alpha_1 d\log(H_1) + (1-\alpha_1)d\log(H_2)\right) = d\log(H_2) + \frac{1}{\sigma_2}d\log(s_2) + d\log(\gamma)$$

whence:

$$\begin{aligned}
\frac{\varepsilon-1}{\varepsilon}\left(\frac{\alpha_1}{\rho} + \frac{(1-\alpha_1)d\log(H_2)}{d\log(\gamma)}\right) &> \frac{\varepsilon-1}{\varepsilon}\left(\alpha_1 d\log(H_1) + (1-\alpha_1)d\log(H_2)\right) \\
&\ge \frac{d\log(H_2)}{d\log(\gamma)} + 1 + \frac{d\log(s_2)}{d\log(\gamma)} \\
\Longrightarrow \left(\frac{\varepsilon-1}{\varepsilon}(1-\alpha_1) - 1\right)\frac{d\log(H_2)}{d\log(\gamma)} &> 1 - \frac{\varepsilon-1}{\varepsilon}\frac{\alpha_1}{\rho} + \frac{1}{\sigma_2}\frac{d\log(s_2)}{d\log(\gamma)}
\end{aligned}$$

The left-hand side of this last inequality is negative and the right hand side is larger than:

$$\frac{1}{\sigma_2\rho} + 1 - \frac{\varepsilon-1}{\varepsilon}\frac{\alpha_1}{\rho},$$

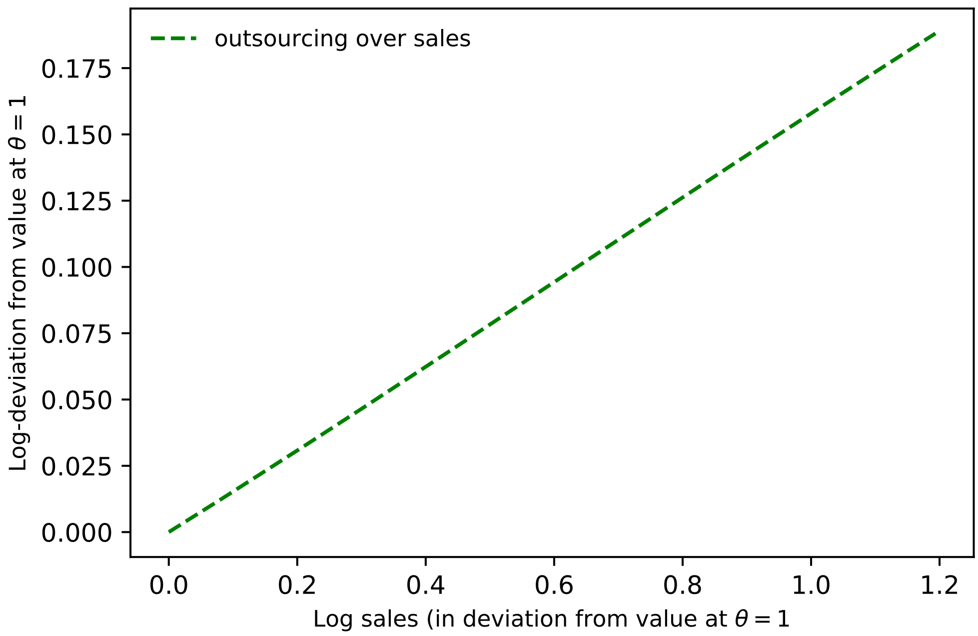
which is positive as long as α_1 is not too large or ρ is not too small. This leads to an impossible statement and hence contradict the assumption that $d\log(n_2)/d\log(\gamma) \ge 1/\rho$.

E.3 Numerical examples

Comparative statics: increase in productivity θ. We consider a specific case with a firm with 4 occupations: 2 high skill ($\alpha_i = 1/3$) and 2 low skill ($\alpha_i = 1/6$), 2 core ($\sigma_i = 0.50$) and 2 non-core occupations ($\sigma_i = 2.5$). In the baseline, we consider that the two dimensions are unrelated. Here, we consider how different variable of interest evolve with respect to θ. We consider the interval $[1,2]$ as the support for θ.[55]

Figure E1 starts by showing the positive relationship between firm size, as measured by sales and outsourcing intensity defined here as the ratio of outsourcing expenditures to sales.

FIGURE E1. Outsourcing intensity as a function of sales following an increase in productivity



Notes: The figure provide comparative statics with respect to an increase in Hicks neutral productivity shifter θ. We consider support the interval $[1,2]$ as support for θ.

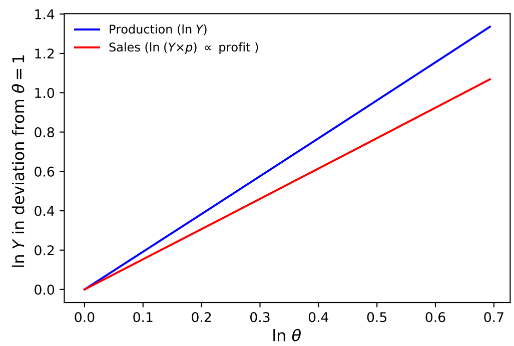
Figure E2 presents a set of results. Panel 2(a) shows how the optimal scale of production and sales evolves as productivity increase. Production Y increases log-linearly with θ, with an elasticity close to 1. Sales, which are proportional to profit in this model, increases also linearly but because the elasticity of demand ε is finite, the revenue / profit function is concave in productivity. Panel 2(b) displays the effect of productivity on the use of in-house and outsourced labor services. Both increase with a roughly constant elasticity (log-linear) but we see that, due to the rising cost of hiring in-house faced by monopsonic employers as they scale-up, they progressively outsource more, resulting in a shrinking in-house to outsourced labor ratio. Panel

[55]The number of occupations is set to 4 so that $\mathbf{N} = \{1,2,3,4\}$. The vector of parameters regarding occupations in production function are as followed: $\boldsymbol{\sigma} = [0.5, 0.5, 2.5, 2.5]$; ; $\boldsymbol{\gamma r} = [0.25, 0.25, 0.25, 0.25]$; $\boldsymbol{\mu} = [.75, .75, .75, .75]$; $\boldsymbol{\alpha} = [1/3, 1/6, 1/3, 1/6]$. Regarding labor supply, we set: $\boldsymbol{\rho} = [1,1,1,1]$, $\mathbf{a} = [1,1,1,1]$. The other parameters are: $\varepsilon = 5, I = 1$ and $N_i = 1, \forall i \in \mathbf{N}$.

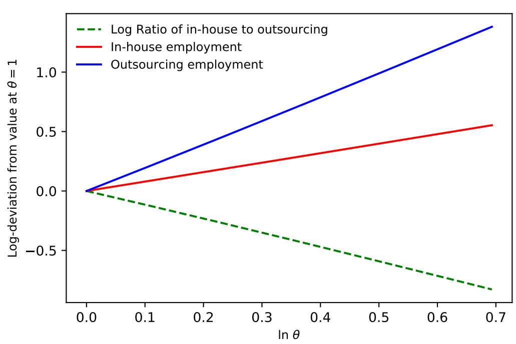
2(c) show that this declining ratio is heterogeneous across occupations. It displays the ratio for a core and non-core occupation with the same weight in the Cobb-Douglas production function. Panel 2(d) makes the same point but focusing on the level of the cost share represented by in-house labor. We see that both shares are high for core occupation and tend to increase with size while the opposite is true of the two non-core occupations.

FIGURE E2. Scale of production, employment and outsourcing as productivity goes up

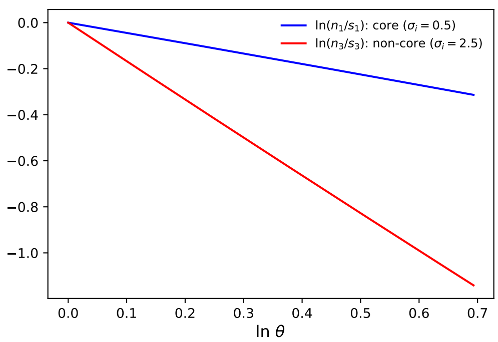
(a) Scale of production



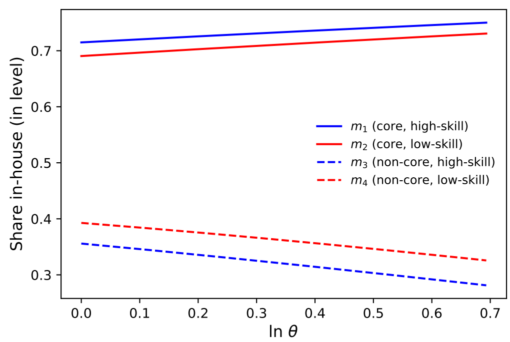
(b) Employment : in-house versus outsourced



(c) In-house ratio in employment, across occupations



(d) In-house cost share, across occupations



Notes: The figure provide comparative statics with respect to an increase in Hicks neutral productivity shifter θ. We consider support the interval $[1,2]$ as support for θ.

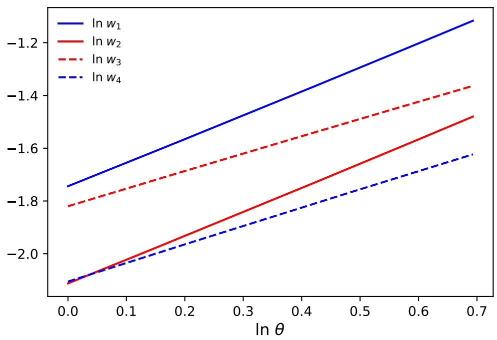
The figure E3 displays four other comparative statics. Panel 3(a) shows the wage in level. Unsurprisingly, high-skill occupations (1 and 3) have the highest wages. We see however that the firm size wage premium is stronger among core occupations independently of skill-level. Panel 3(b) show how log-wage deviates from the initial situation. We see that core and non-core determines almost entirely the magnitude of the elasticity of wage to size. Overall, panels 3(a) and 3(b) are consistent with the empirical existence of a size wage-premium (Oi and Idson, 1999). Moreover, it has been documented that skill-wage premium is stronger in large firms. Through the lenses of our model, this would imply that skills (α_i) tend to be higher in more core occupation (smaller σ_is). Here, we have explicitly made the choice of decorrelating these dimensions, it is plausible however that skill and "core-ness" are positively correlated, in particular if coreness of an occupation is determined by how difficult the tasks it entails are to codify, it seems likely that such tasks might also be requiring high-skill labor and have a high economic return. Correlating these dimensions is straightforward in our model and strengthens the key results displayed below regarding the increase in the share of outsourcing and the increase in occupational specialization. Panel 3(c) compute the HHI index for in-house labor and cost at the firm level across occupations. We see that both employment and cost based HHI increases and that this increase is stronger in terms of costs. This indicates that overall, the firm is concentrating its employment in and spending on in-house labor services on a fewer core occupations. This is a prediction we will be able to test explicitly. Finally, panel 3(d) presents how spending on outsourcing over in-house labor cost (both summed across all occupations) evolves as productivity and scale go up . We do see an increase in this ratio which is somewhat less marked than the equivalent ratio in terms of employment because of the size wage premium associated (see Panel 2(b)) with in-house labor services.

Additional comparative statics. Figure E4 displays similar comparative statics comparing the baseline case and the case ($\rho_i = 1$) with no market power on the in-house labor market ($\rho_i = 0$). It shows see that the in-house cost share per occupation (m_i) and the outsourcing over in-house labor cost ratio does not change with productivity when wage are competitively set, highlighting the key role of labor market frictions in explaining our results.

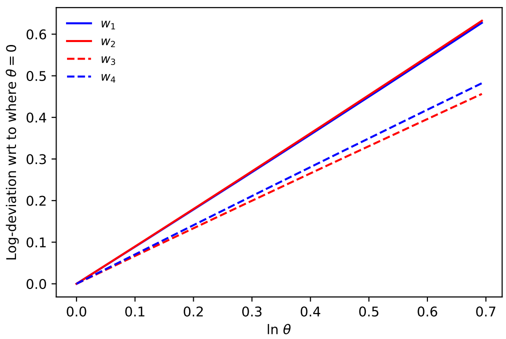
As mentioned above, broadband is also likely to result in a decrease of outsourcing cost, which we capture with a decline in the term γ_{ij}. Decrease in this parameter leads to broadly similar comparative statics as the previous case as displayed in Figure E5.

FIGURE E3. Wage premium, outsourcing over in-house cost and index of occupational segregation (HHI)

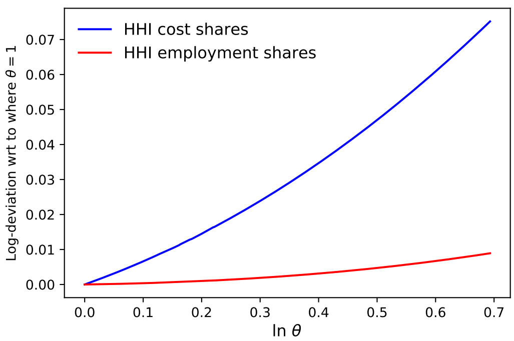
(a) Wage by occupation



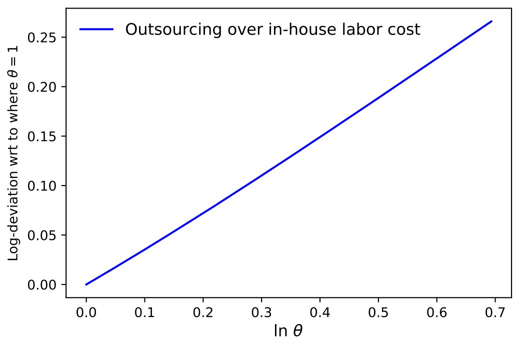
(b) – normalized with respect to $\theta = 1$



(c) HHI in terms of cost shares



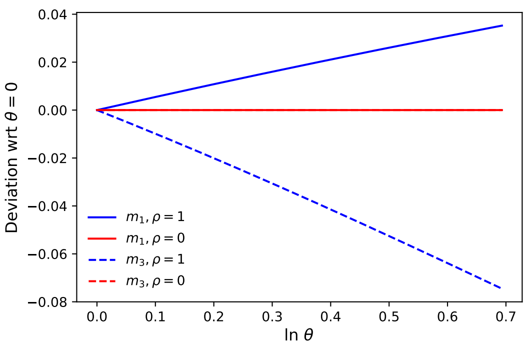
(d) Outsourcing over in house labor cost



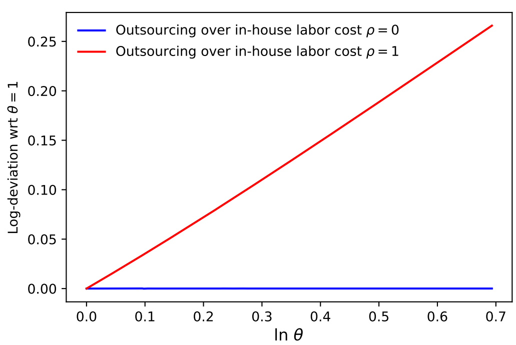
Notes: The figure provide comparative statics with respect to an increase in Hicks neutral productivity shifter θ. We consider support the interval $[1, 2]$ as support for θ.

FIGURE E4. Increase in θ with $\rho_i = 1$ (baseline) and $\rho_i = 0$ (no market power)

(a) Scale of production



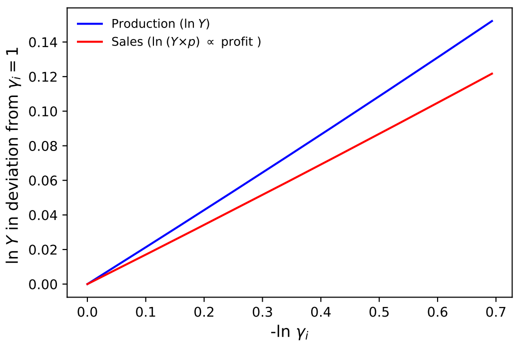
(b) Employment : in-house versus outsourced



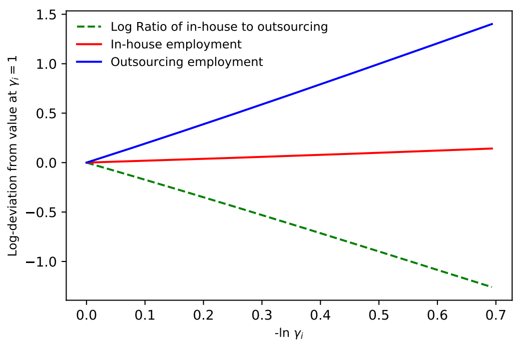
Notes: The figure provide comparative statics with respect to an increase in Hicks neutral productivity shifter θ. We consider support the interval $[1, 2]$ as support for θ.

FIGURE E5. Scale of production, employment and outsourcing as **cost of outsourcing** goes down

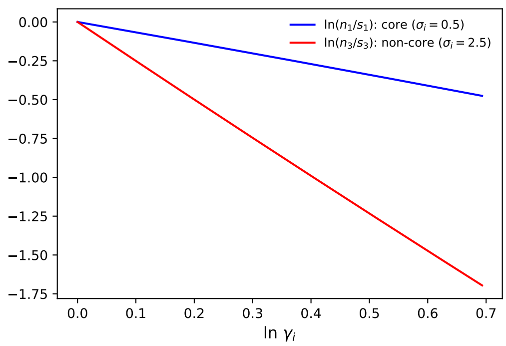
(a) Scale of production



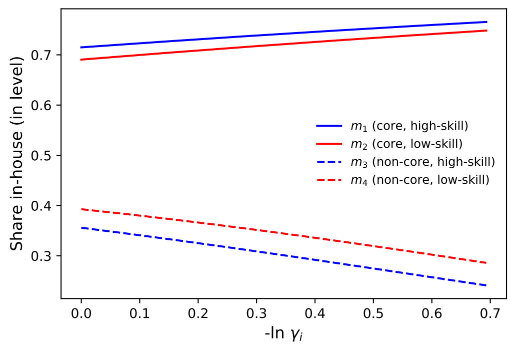
(b) Employment : in-house versus outsourced



(c) In-house ratio in employment, across occupations



(d) In-house cost share, across occupations



Notes: The figure provide comparative statics with respect to an decrease in shifter of outsourcing cost γ_{ij} which occurs uniformly across occupations. We consider $\gamma : 1 \rightarrow 0.5$.