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The Task Content of Occupations*

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The Task Content of Occupations*

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This paper evaluates how an increase in the supply of skilled labor affects task assignment within and between occupations. Guided by a simple theoretical framework, we exploit detailed information about individual workers' tasks from multiple surveys to examine the impact of a twofold rise in the share of university graduates in the French workforce between 1991 and 2013. Our identification strategy uses variation in the change in the graduate share across local labor markets. We find that higher average educational attainment is associated with more routine, fewer cognitive and fewer social tasks within occupations and with fewer routine, more cognitive and more social tasks across occupations.

JEL №: J21, J24, J31.

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1. Introduction

The task approach has attracted considerable attention in labor economics since the seminal work by Autor, Levy and Murnane (2003). Tasks are the building blocks of production. Firms discharge some through machines and contractors. They combine the remainder into jobs, whose content depends on employees' abilities and market conditions. A study of task assignment can thus provide valuable insight into the evolution of labor markets.

Task data are seldom available at the individual level though. Therefore, economists have typically examined jobs after they have been grouped into occupational classifications of mostly administrative origin. This approach treats each occupation as a bundle of tasks, the demand for which shifts with such shocks as automation and offshoring. Yet occupations evolve (Autor, Levy and Murnane, 2003; Levy and Murnane, 1996; Spitz-Oener, 2006). Autor (2015) writes: "As the routine cash-handling tasks of bank tellers receded [...], banks recognized the value of tellers [...] as salespersons, forging relationships with customers and introducing them to additional bank services like credit cards, loans, and investment products." This observation suggests that job content is flexible: firms adapt assignments to changes in the relative costs of production factors, as bank clerks exemplified by assuming more cognitive tasks.[1] In consequence, there is no exact mapping from a job title to a set of tasks (Autor and Handel, 2013): today's tellers share few duties with their counterparts from the 1970s, just as they cater to different clients at multinational banks and regional institutions, yet their jobs receive the same occupational code. Unlike tasks, occupations are not a precise economic concept: they are statistical tools, the result of complex algorithms and specific classifications.

This paper explores the relation between job content and market conditions. In particular, it assesses the impact of changes in the supply of skilled labor in France from 1991 to 2013. Thanks to public investment in higher education, university graduates increased from 18 to 36 percent of the workforce over this period. We exploit individual data from five surveys of work conditions, which allows us to compare jobs within occupations. Table 1 in Section 2 presents our task measures. Following the literature, we group them into three indexes for analysis: routine, cognitive and social.

Our argument is threefold. First, job content is heterogeneous within occupations (Autor and Handel, 2013). For example, consider again bank clerks. Figure 1 displays the variation in the number of tasks by category. If we divide the subsample by task set, no cell contains more than 13 percent of tellers and 90 percent report tasks in multiple categories. Second, university graduates hold a comparative advantage in cognitive duties (Acemoglu and Autor, 2011; Spitz-Oener, 2006). Third, the skill premium fell with the expansion of higher education, so firms were more willing to hire skilled workers and assign them routine activities in spite of their comparative disadvantage. Figure 1 illustrates this shift: bank clerks were given more routine and fewer cognitive tasks as the share of university graduates among them rose from 14 percent in 1991 to 58 in 2013.

Section 4 formalizes these ideas into a model. Workers supply one unit of labor, which they share between a routine and a cognitive task. Skilled workers hold a comparative advantage

1 We use "job content" as a synonym for workers' tasks throughout the paper.

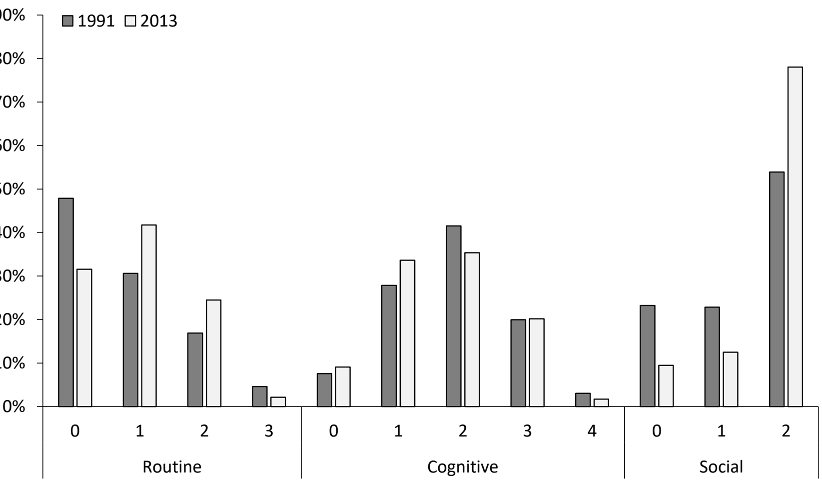

Figure 1: Distribution of the sum of task indicators for bank clerks by year

Notes: Section 2 discusses task categories. *Sources:* Authors' calculations, based on the Work Conditions Survey by INSEE and DARES.

in the cognitive task. Unlike Autor, Levy and Murnane (2003) or Acemoglu and Autor (2011) (but in line with the data), we assume that workers do not specialize. Firms combine tasks into output. The model predicts two effects from an increase in the supply of skilled workers. Because they perform more cognitive work than the unskilled, a composition effect raises the cognitive content of aggregate output. On the other hand, a substitution effect obtains at the individual level as each worker executes more routine tasks in response to the change in relative task prices.

We test these predictions by regressing our task indexes on the share of university graduates by occupation, region and year. Since schooling, migration and labor supply are endogenous, we project the graduate share on the basis of previous surveys to construct instruments. The first is the graduate share among workers who will still be under the minimum retirement age by the next survey. The second supposes that the regional contingents of the skilled and the unskilled will evolve at the national rate between surveys (Bartik, 1991). We define both instruments in terms of birth regions rather than region of residence on account of migration. Identification hinges on the assumption that initial workforce compositions are orthogonal to temporary local shocks (Goldsmith-Pinkham, Sorkin and Swift, 2018). (We include fixed effects for education, region and year.)

Our results are twofold. For a given occupation, a higher graduate share is associated with more routine, fewer cognitive and fewer social tasks. The opposite pattern holds across occupations: the average job involves fewer routine, more cognitive and more social tasks. Therefore, we find evidence for both theoretical predictions of an individual substitution effect and an aggregate composition effect. The estimates are significant but modest: the task indexes shift by 3 to 13 percent of a standard deviation for a rise in the graduate share of 10 percentage points around the mean.

We examine task compensation as well. We show that an increase in the cognitive index of one standard deviation raises hourly wages by two percent, an increase in the routine index decreases hourly wages by 0.4 percent and an increase in the social index decreases hourly wages by 0.4 percent. These estimates are similar to Autor and Handel's (2013), though theirs are based on different measures of job content and American data. Our results confirm that task assignment affects pay within occupations.

The task literature has greatly improved our understanding of labor markets. For example, Autor, Levy and Murnane (2003) argue that computers replaced labor in routine activities, raising the cognitive content of occupations and reshaping the occupational structure within industries. Similar analyses have shed light on employment polarization (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Autor, Dorn and Hanson, 2015; Autor, Katz and Kearney, 2006; Firpo, Fortin and Lemieux, 2011), gender gaps (Black and Spitz-Oener, 2010), immigration (Peri and Sparber, 2009), mobility (Gathmann and Schönberg, 2010), offshoring (Blinder, 2009; Jensen and Kletzer, 2010), social skills (Deming, 2017) and more. This paper shows that market conditions influence task assignment within occupations. This finding highlights the need for nuance in discussing the future of work (Acemoglu and Restrepo, 2018a,b). It does not suffice to examine the typical tasks in an occupation at present to forecast its susceptibility to automation or outsourcing. As we noted earlier, occupations evolve: workers may perform unautomated tasks more intensively, firms may develop new tasks for idle employees, etc. Rising educational attainment may facilitate this adjustment by preparing workers for lifelong learning and flexible roles.

The paper continues as follows. Section 2 presents the data. Section 3 discusses stylized facts. Section 4 introduces the model. Section 5 describes our empirical approach. Section 6 contains the results. Section 7 concludes.

2. Data

This section describes our data. Our sources are the French Labor Force Survey (*Enquête Emploi*, LFS), the Work Conditions Survey (*Enquête Conditions de Travail*, WCS) and the Work Organization Survey (*Enquête Techniques et Organisation du Travail*, WOS).

2.1. The Labor Force Survey

The National Institute of Statistics and Economic Studies (*Institut national de la statistique et des études économiques*, INSEE) developed the survey in 1950 in an effort to measure employment between census years (Goux, 2003). It was mostly yearly until 2002. It averaged 146 000 respondents per year between 1990 and 2002, renewed by thirds. Data collection became continuous in 2003. Results are quarterly. The sample averaged 71 500 respondents per quarter between 2002 and 2008, renewed by sixths. It increased over 2009 to an average of 104 000 respondents per quarter between 2010 and 2012.

The LFS collects information about workers' characteristics, their jobs and their households. We construct the following covariates for the empirical analysis: female; married; foreign born; age and age squared; tenure and tenure squared; multiple jobs; part-time job; fixed-term contract; and civil servant. Except for age and tenure, all covariates are binary indicators.

Furthermore, we include fixed effects for education,[2] occupation and region of residence.[3] We use two-digit occupations, since the four-digit classification changed in 2003. We do not include industry effects because the classification changed in 1993 and 2008. Other than covariates, the LFS gives us the share of university graduates by region and occupation. Because certain cells are small, we pool observations across three years at a time for additional precision. For example, we estimate the graduate share in 1991 with data from 1990–92.

The LFS gathers data about monthly wages after tax. A third of respondents provide intervals instead of precise numbers. A small percentage refuses to answer at all (less than three percent of wage workers). INSEE imputes wages for these observations. The resulting distribution is similar to the distribution across the *déclarations annuelles de données sociales* (the reference for French wage data). Because of the reduction of the workweek from 39 to 35 hours between 1999 and 2002, monthly wages are not directly comparable across years. Therefore, we use weekly hours to construct hourly wages.[4] We truncate hours at the legal limit (60 hours per week). We also adjust them if the employer extended holidays in lieu of shortening the workweek. If the respondent reported an interval, we use its half point. If they did not answer at all, we use the median by occupational and part-time status.

We restrict the sample to wage workers by excluding interns, apprentices, artisans, agricultural workers, the self-employed, business owners and the clergy. Wage regressions exclude workers whose hourly wages are smaller than four fifths of the minimum wage or outliers.[5] We use sampling weights throughout the paper. We normalize the sum of weights across the final sample of each year to unity.

2.2. The Work Conditions Survey (WCS) and the Work Organization Survey (WOS)

INSEE conducted its first WCS in 1984. A supplementary survey of the outgoing group of the LFS, it enquired into sources of stress at work, whether physical (e.g., loud noises) or psychological (e.g., interacting with the public). INSEE repeated the exercise in 1991, 1998 and 2005. The WOS was a similar supplement to the LFS, focused on job content and the organization of work. It was undertaken in 1987 and 1993. The WCS and WOS averaged 20 000 respondents per wave. The Directorate for Research, Studies and Statistics at the Labor Ministry (*Direction de l'animation de la recherche, des études et des statistiques*, DARES) took responsibility over the WCS in 2013. It became an independent survey and involved 33 673 respondents in its first wave.

Researchers have often drawn task data from two sources from the US: the Dictionary of Occupational Titles and the O*NET. Both files provide scores for a large number of occupations in terms of activities, aptitudes and requirements (Autor, Levy and Murnane, 2003; Jensen and Kletzer, 2010). The WCS and WOS offer a significant advantage over these data: access to

2 We group education levels into: less than middle school, middle school, high school, college and postgraduate.

3 Because the sample contains few observations from Corsica, we merge it into Provence. In constructing the instrument, we use regions of birth. We create a synthetic region for the foreign born.

4 The yearly survey collected information about regular weekly hours. The quarterly survey has distinguished between contractual hours and regular hours. We use contractual hours when they are available.

5 Following Crépon and Gianella (1999), outliers are observations for which $|u - q_{50}| > 5 \times (q_{75} - q_{25})$, where u is the residual from a linear regression of log hourly wages and q_x is x-th centile of log hourly wages. The regression uses data from the LFS between 1990 and 2012.

TABLE 1: PERCENTAGE OF POSITIVE RESPONSES BY TASK MEASURE AND YEAR

	1991	1993	1998	2005	2013	All
Routine tasks						
Production norms to be fulfilled within the day	38.0	42.6	43.0	42.1	45.9	42.3
Repetitive movements	29.6	24.5	28.7	27.9	41.2	30.4
Work rhythm determined by machinery	12.8	11.5	13.6	13.9	18.0	14.0
Cognitive tasks						
Choosing strategy to achieve goals	83.5	83.9	86.9	81.4	80.2	83.2
Departing from deadlines	35.7	37.1	36.2	36.6	34.3	36.0
Departing from instructions	24.6	22.4	28.0	30.3	28.2	26.7
Handling incidents	50.2	53.4	56.6	52.1	50.7	52.6
Social tasks						
Contact with the public	60.7	61.3	62.4	68.5	70.9	64.8
Work rhythm determined by external demands	45.9	45.0	54.3	53.5	58.0	51.4

individual responses. As a consequence, we can explore heterogeneity within occupations and the joint task distribution across workers. (Similar samples are available for Germany: see Spitz-Oener (2006). See also Autor and Handel (2013).)

We measure job content along three dimensions: routine, cognitive and social. We borrow this approach from the extensive literature on automation and offshoring (Autor, Levy and Murnane, 2003; Firpo, Fortin and Lemieux, 2011; Jensen and Kletzer, 2010). Following Spitz-Oener (2006), we construct task indexes by selecting relevant variables from the WCS and the WOS,[6] transforming them into indicators and averaging the indicators. Table 1 shows the means of each indicator by category and year. Routine tasks denote a lack of autonomy or a submission to machinery. Cognitive tasks involve decision making. Social tasks require interaction with clients or the public. Note that we limit the sample to the period from 1991 to 2013. We discard the 1984 WCS and the 1987 WOS because the LFS did not contain all of the variables of interest at the time. See Section 3 for further discussion.

3. Stylized facts

This section presents stylized facts about the French labor market. We focus on the expansion in higher education and task assignment.

Figure 2 plots the graduate share among employed workers across years. It doubled from 18 percent in 1990 to 36 in 2012. There was a concomitant increase in the proportion of workers with secondary degrees from 12 to 19 percent, whereas the fraction of workers without degrees fell from 41 to 20 percent. The skill premium declined as well: as the graph shows, university graduates' median hourly wage was 38 percent larger than other workers' in 2012, against 66 percent in 1990. These trends were partly due to sustained public investment in higher education. As education minister under François Mitterrand, Jean-Pierre Chevènement initiated an effort to raise the graduation rate from high school to 80 percent in the mid 1980s.

6 We selected variables on two criteria: they should unambiguously pertain to one of the three categories and they should be available across all years.

Modernization plans for tertiary education followed in 1990 (*Plan Université 2000*) and 1999 (*Plan Université du troisième millénaire*), which included the creation of eight universities and dozens of technical colleges.

The skill supply may influence task assignment within firms in equilibrium. Figure 3 displays average task indexes by education level in 1991 and 2013. As Spitz-Oener (2006) noted, university graduates perform fewer routine, more cognitive and more social tasks than other workers. However, these differences softened over time. Routine activities became common for both groups, but the proportional increase was larger for graduates. We find the same pattern in social tasks. While there was little change in cognitive tasks for nongraduates, we observe a reduction for graduates.[7] As we argue in Sections 4 and 6, the expansion of higher education may partly explain these adjustments: given the lower skill premium, firms may have been more willing to hire skilled workers and assign them routine tasks.

Tables 2 and 3 further characterize the evolution of job content in France. Table 2 confirms the growth in the incidence of routine and social tasks, whereas cognitive tasks remained stable in aggregate over the sample period. We observe little change in standard deviations. Moreover, the table reveals that covariates offer limited insight into this dispersion. It shows the coefficient of determination from linear regressions of task indexes on individual characteristics and fixed effects for education level, occupation and region. This model explains a quarter of the variation in task assignment at most. This finding provides additional evidence that job content is heterogeneous within occupations (Autor and Handel, 2013). Table 3 summarizes changes in job content by decile of hourly wages from 1991 to 2005. Note first that we find no sign of rising inequality in France: as the last row shows, the ratio of the ninth decile to the first shrank by 8 percent between 1991 and 2005.[8] Second, routine tasks are more frequent in the bottom of the wage distribution by our measure, whereas social and especially cognitive tasks are more common in the top. Third, this pattern has become looser over time. The ratio of the average routine score in the ninth wage decile to the average in the first increased by 18 percent between 1991 and 2005. The ratio of cognitive scores decreased by 15 percent. The ratio of social scores decreased by 10 percent.[9] It is interesting that wage inequality fell at the same time as the correlation weakened between tasks and pay. The link between these trends is a topic for future research.

We conclude this section with an overview of the economic background in the 1990s and 2000s. Growth was slow and unsteady. Real GDP per capita expanded at an average yearly rate of 1.8 percent between 1990 and 2013. There were four recessions in this period (in 1992, 2001, 2008 and 2012). Unemployment was persistently high, averaging 8.8 percent, and the shares of both fixed-term contracts and part-time jobs increased (from 6 to 11 percent and from 11 to 17 percent, respectively). These decades are also noteworthy for the reduction of the legal workweek from 39 to 35 hours between 2000 and 2002, which inflated hourly wages and compressed their distribution (Aeberhardt, Givord and Marbot, 2016).

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7 Spitz-Oener (2006) finds different patterns in Germany. Nonroutine tasks became more common at all education levels, but the proportional change was larger for the uneducated. Routine manual tasks exhibit a larger decrease for the uneducated as well. On the other hand, she observes a larger cut in routine cognitive tasks for the educated. It is unclear whether these discrepancies are due to fundamentals or differences in task indexes.

8 For further discussion, see Bozio, Breda and Guillot (2016) and the references therein.

9 The table focuses on the period from 1991 to 2005 because the 2013 WCS did not collect comparable wage data.

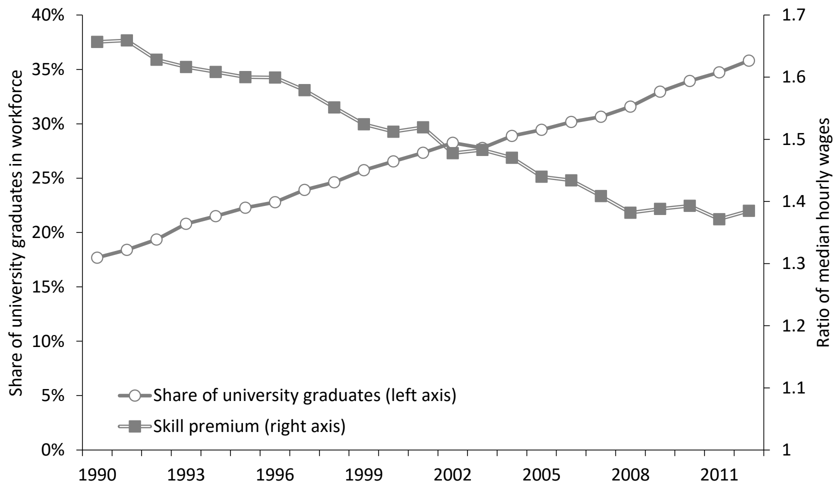

Figure 2: Share of university graduates and skill premium by year

Notes: The sample consist of employed wage workers. The skill premium is the ratio of median hourly wages of university graduates and less educated workers. *Sources:* Authors' calculations, based on the Labor Force Survey by INSEE.

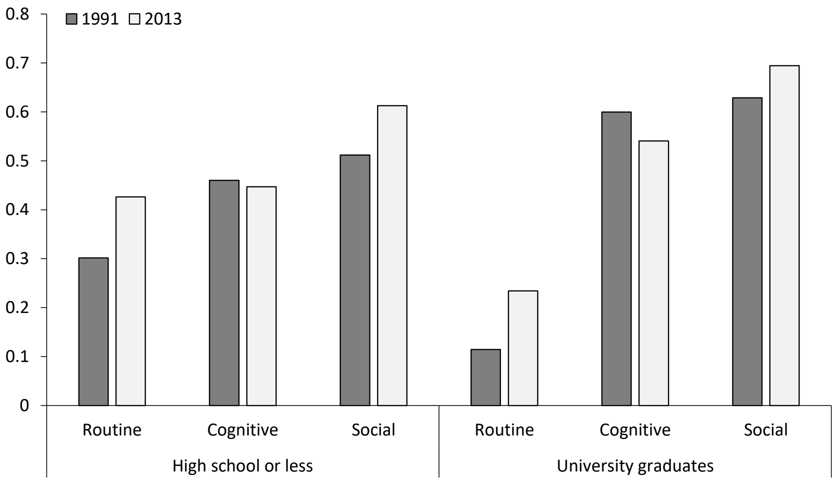

Figure 3: Change in task assignment by education level

Notes: The figure shows the average of task indicators in each group by education level and year (q.v. Section 2). *Sources:* Authors' calculations, based on the Work Conditions Survey by INSEE and DARES.

TABLE 2: VARIATION IN TASK ASSIGNMENT

	Routine tasks			Cognitive tasks			Social tasks		
	Mean	St. dev.	R^2	Mean	St. dev.	R^2	Mean	St. dev.	R^2
1991	0.268	0.305	0.228	0.485	0.272	0.200	0.533	0.415	0.246
1993	0.262	0.300	0.231	0.492	0.257	0.178	0.532	0.405	0.180
1998	0.284	0.309	0.243	0.519	0.259	0.164	0.584	0.405	0.196
2005	0.280	0.309	0.203	0.501	0.267	0.119	0.610	0.393	0.154
2013	0.350	0.327	0.217	0.484	0.265	0.151	0.645	0.377	0.175
All	0.289	0.312	0.223	0.496	0.264	0.156	0.581	0.402	0.193

Notes: The table shows summary statistics for the average of task indicators in each group (q.v. Section 2). The R^2 refers to a linear regression on individual characteristics and fixed effects (education, occupation, region and year).

TABLE 3: TASK ASSIGNMENT AND HOURLY WAGES BY DECILE OF HOURLY WAGES

Decile	Hourly wages		Routine tasks		Cognitive tasks		Social tasks	
	Level, 1991	Change, 91–05	Level, 1991	Change, 91–05	Level, 1991	Change, 91–05	Level, 1991	Change, 91–05
1	6.625	0.215	0.336	−0.011	0.396	0.123	0.482	0.220
2	7.494	0.193	0.327	−0.002	0.409	0.109	0.495	0.202
3	8.351	0.181	0.317	0.008	0.424	0.092	0.507	0.187
4	9.207	0.168	0.302	0.028	0.445	0.065	0.520	0.169
5	10.192	0.151	0.287	0.042	0.464	0.049	0.531	0.156
6	11.246	0.154	0.267	0.060	0.489	0.033	0.544	0.142
7	12.712	0.154	0.240	0.084	0.521	0.016	0.559	0.125
8	14.988	0.142	0.202	0.117	0.562	−0.008	0.573	0.109
9	19.485	0.114	0.151	0.171	0.627	−0.047	0.583	0.094
9/1	2.941	−0.083	0.449	0.184	1.583	−0.151	1.210	−0.104

Notes: Wages are shown in constant euros (base 2015). The table shows average task indexes within each wage decile and the proportional change in averages from 1991 to 2005. The last row shows the ratio between the expectation in the last decile and the mean index in the first decile. Expectations were estimated through a first-order local polynomial.
Sources: Authors' calculations, based on the Labor Force Survey and the Work Conditions Survey by INSEE.

4. Theoretical framework

This section develops a simple theoretical framework for our empirical analysis of the interaction between the supply of skilled workers and task assignment. We adapt the model by Peri and Sparber (2009).

4.1. Task demand

Consider an economy in autarchy. A representative firm combines tasks into a consumption good (y). Tasks may be routine (r) or cognitive (c). For simplicity, we assume that production does not require capital. The production technology is:

$$y = \left[r^{(\sigma-1)/\sigma} + c^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)},$$

where σ controls the elasticity of substitution between inputs (n.b. $\sigma > 0$).[10] Production does not require both tasks (unless $\sigma \to 1$), but this functional form implies that the firm will always mix them in equilibrium, as we observe in the data (cf. Section 2).

The firm purchases task services on frictionless labor markets. The consumption good is the numeraire. Therefore, profits are: $y - w_r r - w_c c$, where w_r is the price of a unit of routine tasks (analogously for w_c). By combining the necessary conditions for profit maximization, we find the relative demand for tasks:

$$\frac{\hat{r}(\omega)}{\hat{c}(\omega)} = \frac{1}{\omega^{\sigma}}, \tag{1}$$

where ω is the price ratio: $\omega \equiv w_r/w_c$. The firm decreases the routine content of production in response to an increase in the cost of routine tasks. This inverse relationship is important for our results, though its precise functional form is not.

4.2. Task supply

The economy comprises a measure p of skilled workers ($s = 1$) and a measure $1 - p$ of unskilled workers ($s = 0$). Each worker is endowed with one unit of labor. They do not derive utility from leisure. Hence, they apportion x_s of their time to the supply of r_s in routine tasks and $1 - x_s$ to the supply of c_s in cognitive tasks. The resulting task supply is:

$$r_s = \alpha_{rs} x_s^{\beta} \quad \text{and} \quad c_s = \alpha_{cs}(1 - x_s)^{\beta}, \tag{2}$$

where $\beta \in (0, 1)$ and $\alpha_{\cdot s} > 0$. The curvature parameter β implies that workers become less productive as they repeat tasks, which may reflect technical limitations (e.g., fatigue) or a preference for variety at work. The scale parameter $\alpha_{\cdot s}$ captures total productivity. We assume that skilled workers enjoy a relative advantage at cognitive tasks: $\alpha_{c1}/\alpha_{r1} > \alpha_{c0}/\alpha_{r0}$.

Because savings bear no interest and the model is static, workers do not save. Therefore, they maximize utility by maximizing their income,

$$w_r \alpha_{rs} x_s^{\beta} + w_c \alpha_{cs}(1 - x_s)^{\beta},$$

10 See Acemoglu and Autor (2011) for a discussion of this production function.

through the choice of x_s. The optimal allocation ($\hat{x}_s(\omega)$) satisfies:

$$\frac{\hat{x}_s(\omega)}{1-\hat{x}_s(\omega)} = \left(\frac{\alpha_{rs}\omega}{\alpha_{cs}}\right)^{\frac{1}{1-\beta}}, \tag{3}$$

where $\hat{x}_s(\cdot)$ is an increasing function.

Equation (3) has three implications. First, the supply of routine tasks increases with their relative price. Second, the unskilled perform more routine tasks than the skilled: $r_0 > r_1$. Conversely, $c_1 > c_0$. This property is due to their relative advantages and finds support in the data (cf. Figure 3). Third, workers do not specialize: $r_s > 0$ and $c_s > 0$ for all s. This feature is a consequence of the nonlinearity in task supply (cf. equation (2)). The data support it as well: fewer than 15 percent of workers in our sample report tasks in a single category. Our model differs from Acemoglu and Autor's (2011) or Autor, Levy and Murnane's (2003), where task production is linear and each worker specializes in a single task.

4.3. *Equilibrium and comparative statics*

Equilibrium obtains when prices, w_r and w_c, ensure that each task market and the goods market clear:

$$\begin{aligned}
r &= (1-p)r_0 + pr_1, \\
c &= (1-p)c_0 + pc_1, \\
y &= w_r[(1-p)r_0 + pr_1] + w_c[(1-p)c_0 + pc_1].
\end{aligned}$$

We can find the equilibrium in two steps. Equations (1) and (3) fix relative prices. We can then determine absolute prices by clearing the goods markets.

This paper investigates the impact of changes in the supply of skilled labor on task assignment. The model has implications for our empirical analysis. To find them, we first combine equations (1) and (3):

$$\frac{(1-p)\alpha_{r0}\hat{x}_0(\omega)^\beta + p\alpha_{r1}\hat{x}_1(\omega)^\beta}{(1-p)\alpha_{c0}[1-\hat{x}_0(\omega)]^\beta + p\alpha_{c1}[1-\hat{x}_1(\omega)]^\beta} = \frac{1}{\omega^\sigma}.$$

Implicit differentiation then reveals that the price ratio, ω, is an increasing function of the share of skilled workers, p.[11] For a fixed ω, a higher p induces an increase in the supply of cognitive tasks, since skilled workers perform more cognitive tasks than the unskilled. Equilibrium requires that cognitive tasks become relatively cheaper, so ω must rise. (Note that an increase in ω entails a falling skill premium: cf. Figure 2.) The new equilibrium differs in two aspects. Workers exert more routine and fewer cognitive tasks: there is a substitution effect toward the routine by equation (3). Nonetheless, equation (1) implies that the cognitive content of aggregate output increases by a composition effect. These effects are generally nonlinear with respect to the share of skilled workers and the magnitude of the shift in p between equilibria.

11 The proof is available from the authors upon request.

To develop intuition, it is useful to adopt the perspective of the firm. If the skill supply grows, cognitive tasks become relatively abundant (hence, cheaper). The firm has an incentive to use more cognitive tasks, so it hires more skilled labor. This shift is the composition effect. However, it does not completely replace its former unskilled workers' routine duties with cognitive activities. Because they now pay less, workers are less keen on cognitive assignments. Therefore, the firm keeps some routine tasks, which it distributes across remaining unskilled employees and their skilled colleagues. This adjustment is the substitution effect.

We have assumed that there are distinct task markets and that workers control task supply. We could rewrite the model so that markets separate by skill and firms assign tasks to their employees. Although the exposition is more cumbersome, the key mechanism remains and our results go through: an increase in the skill supply would again shrink the skill premium, generating a substitution effect at the worker level and a countervailing composition effect at the aggregate level.

5. Empirical approach

This paper explores the impact of shifts in the skill supply on task assignment. Our model suggests that an increase in the share of skilled workers should correlate with more routine tasks at the individual level and fewer at the aggregate level. To evaluate these predictions, we compare workers' task scores within labor markets across years. Although the model does not feature social tasks, we include them in the empirical analysis for completeness.

We assume that workers segregate into distinct labor markets by administrative region and two-digit occupation. Our analysis comprises 483 markets by this definition.[12] We use the share of university graduates as a proxy for the skill supply.

Consider observation i in occupation o, region r and year t. Write y_{iort} for the task score in question, p_{crt} for the graduate share, $\boldsymbol{x}_{icrt}$ for a vector of individual characteristics and u_{icrt} for the residual. (See Section 2 for a description of covariates.) We estimate:

$$y_{iort} = \gamma_1 p_{ort} + \gamma_2 p_{ort}^2 + \boldsymbol{\beta}^\top \boldsymbol{x}_{iort} + \alpha_o + \alpha_r + \alpha_t + \alpha + u_{iort}. \tag{4}$$

We are interested in γ_1 and γ_2. The quadratic term helps us take nonlinearities into account (cf. Subsection 4.3).

Ordinary least squares need not yield consistent estimates of γ_1 and γ_2. One concern is measurement error, since we estimate the graduate share from the LFS. Although we pool observations across three years for additional precision (see Section 2), we may still lack power for some occupations in less populated regions. Another concern is endogeneity in schooling decisions, migration patterns and workforce participation. For example, a local technological shock could affect both the relative demand for cognitive tasks (because routine tasks are automated, say) and the skilled supply (because skilled workers immigrate from other regions, say).

Therefore, we use instrumental variables for identification. We construct two instruments by projecting the graduate share on the basis of earlier waves of the LFS. For concreteness, consider observation i from 1991. We use three surveys to compute the instruments: 1983,

12 In French terminology, we define markets in terms of *régions* and *catégories socioprofessionnelles*.

1984 and 1985.[13] The first instrument exploits retirements: it is the graduate share among such workers as were born in the same region as i, exert the same occupation as i and will not reach the minimum retirement age by 1991 (viz. 60 years). This definition helps us cancel the effect of endogenous migration and the schooling decisions of incoming cohorts. It does not involve actual retirements, lest we introduce bias. This instrument is relevant because retirements boosted the share of graduates in the workforce in this period by eliminating less educated cohorts (cf. Section 3). The second is a Bartik instrument (Bartik, 1991). It is the hypothetical graduate share among such workers as were born in the same region as i and exert the same occupation as i if the contingents of graduates and nongraduates had each evolved at the corresponding national rate between surveys. The exclusion restriction depends on the same assumption for both instruments: initial education levels and national graduation trends must be orthogonal to local shocks (Goldsmith-Pinkham, Sorkin and Swift, 2018). Note that our regressions include fixed effects for region and year. Hence, we obtain identification from variation in the change in the graduate share across labor markets. The region effects help us account for structural differences between markets, while the year effects capture common shocks (e.g., the business cycle).

Table 4 shows coefficients from linear regressions of the graduate share on the instruments. Both are highly correlated with the graduate share. The Bartik instrument is slightly stronger, perhaps because it takes the average education of incoming cohorts into account. Covariates reduce the coefficients, but they remain significant at any conventional level.[14]

6. Results

6.1. The impact of the skill supply on task assignment

Table 5 displays our main results: estimates of the impact of changes in the graduate share on job content (per equation (4)). Each column presents one combination of task index and covariates. The first two columns show coefficients from regressions of the routine score; columns (3) and (4), of the cognitive score; columns (5) and (6), of the social score; the last two columns, of the ratio between the routine score and the sum of the three scores.[15] Odd columns display coefficients from regressions with fixed effects for occupation; even columns, without them. Each column contains estimates by two-stage least squares and ordinary least squares.[16] For the sake of parsimony, the table only shows results for the retirement instrument. Table 7 in Appendix A presents equivalent estimates for the Bartik instrument. Our conclusions are robust to the choice of instrument.[17]

13 For 1993, we use data from 1983–85 as well. For 1998, we use data from 1990–92. For 2005, we use data from 1997–99. For 2013, we use data from 2004–06. We update the base year for symmetry.

14 Even columns use fewer observations than odd columns because we do not observe tenure for all observations. Our estimates are robust to dropping incomplete observations altogether or imputing tenure.

15 Note that columns (7) and (8) exclude 661 observations for which the sum of task indexes is zero.

16 Because the regression equation is quadratic (q.v. equation (4)), we use the instrument and its square.

17 We do not use both instruments together for two reasons: first, they are so unfortunately correlated that we gain little power (the correlation is 0.99); second, the comparison of the results for each instrument helps us assess the robustness of our estimates.

TABLE 4: LINEAR REGRESSION OF THE GRADUATE SHARE ON INSTRUMENTS

	(1)	(2)	(3)	(4)
Retirement instrument	1.000***	0.411***		
	(0.001)	(0.005)		
Bartik instrument			0.988***	0.465***
			(0.001)	(0.005)
Partial F-statistic	1.2×10^6	8,129	2.0×10^6	11,064
Controls				
Individual characteristics		11		11
Education fixed effects		4		4
Occupation fixed effects		22		22
Region fixed effects		20		20
Year fixed effects		4		4
Fit				
Observations	94,990	94,253	94,990	94,253
Parameters	1	62	1	62
Adjusted R^2	0.963	0.980	0.972	0.982

Notes: The table shows coefficients from ordinary linear regressions. Standard errors (in parentheses) are robust to heteroscedasticity. The outcome is the share of university graduates by occupation, region and year. Both instruments are a projection of the share of graduates by birth region and occupation. The retirement instrument supposes that the graduate share will only evolve between surveys because of retirements. The Bartik instrument supposes that the contingents of graduates and nongraduates will evolve at the national rate in each local market between surveys. See Section 5 for further detail. The partial F-statistic tests the joint significance of the instruments. *Legend:* Stars denote significance: *, at the 10 percent level; **, 5 percent; ***, 1 percent.

TABLE 5: IMPACT OF CHANGES IN THE GRADUATE SHARE ON TASK ASSIGNMENT

	Routine tasks		Cognitive tasks		Social tasks		Routine tasks (share)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Retirement instrument								
Share of university graduates	0.321***	−0.610***	−0.128***	0.465***	−0.054	0.786***	0.153***	−0.624***
by occupation, region and year	(0.064)	(0.018)	(0.061)	(0.016)	(0.089)	(0.025)	(0.043)	(0.013)
Squared share of university graduates	−0.501***	0.451***	−0.354***	−0.360***	−0.235***	−0.727***	−0.066	0.510***
by occupation, region and year	(0.074)	(0.020)	(0.079)	(0.019)	(0.118)	(0.029)	(0.051)	(0.014)
No instrument								
Share of university graduates	0.108**	−0.667***	−0.103**	0.458***	−0.044	0.871***	0.067**	−0.670***
by occupation, region and year	(0.045)	(0.016)	(0.040)	(0.014)	(0.058)	(0.022)	(0.030)	(0.012)
Squared share of university graduates	−0.164***	0.521***	−0.021	−0.350***	−0.225***	−0.824***	−0.029	0.563***
by occupation, region and year	(0.040)	(0.018)	(0.040)	(0.017)	(0.059)	(0.025)	(0.027)	(0.013)
Controls								
Individual characteristics	11	11	11	11	11	11	11	11
Education fixed effects	4	4	4	4	4	4	4	4
Occupation fixed effects	22		22		22		22	
Region fixed effects	20	20	20	20	20	20	20	20
Year fixed effects	4	4	4	4	4	4	4	4
Fit								
Observations	94,253	94,253	94,253	94,253	94,253	94,253	93,592	93,592
Parameters	63	41	63	41	63	41	63	41
Adjusted R^2 (OLS)	0.223	0.150	0.156	0.117	0.194	0.086	0.305	0.178

Notes: Standard errors (in parentheses) are robust to heteroscedasticity. The share of routine tasks is the ratio of routine tasks to the sum of task indexes. See Section 2 for a description of the task indexes. The instrument is a projection of the share of graduates by birth region and occupation (q.v. Section 5). It supposes that the graduate share will only evolve between surveys because of retirements. *Legend:* Stars denote significance: *, at the 10 percent level; **, 5 percent; ***, 1 percent.

Our estimates may be difficult to interpret because of the quadratic term in equation (4). To facilitate the discussion, define the standardized effect as the change in a given task index for an increase of ten percentage points in the graduate share around the nationwide share in 1990 (from 13 to 23 percent), as implied by two-stage least squares.

Consider routine tasks first. As column (1) shows, the effect of an increase in the graduate share on routine tasks is concave within occupations. By the causal estimates, it peaks when the graduate share nears 32 percent and turns negative when it reaches 64 percent. Since the nationwide graduate share was 18 percent in 1991, we conclude that rising educational attainment caused an increase in the routine job content in France, which corroborates the prediction of a substitution effect at the worker level from our model. Recall that the substitution effect occurs because workers earn relatively more for routine tasks after an expansion in the skill supply. The magnitude is modest: the standardized effect is 0.014 or 4.6 percent of a standard deviation.[18] The causal coefficients are larger than the estimates by linear regression, but they agree in direction. Column (2) repeats this exercise without occupation indicators. We find the opposite pattern: the impact of an increase in the graduate share is convex and uniformly negative, bottoming out when the graduate share is just shy of 68 percent. Unlike the previous regression, this specification does not hold the occupational composition constant within regions. Therefore, it captures a mixture of the change in the routine content of occupations and growing employment in cognitive occupations (in which skilled workers specialize). It constitutes evidence of the composition effect in the model. The standardized effect is –0.045 (14.4 percent of a standard deviation).

As theory predicts, cognitive tasks mirror the routine. Column (3) implies that the impact of an expansion in the graduate share on the cognitive score is negative and concave within occupations. The standardized effect is –0.025 (9.6 percent of a standard deviation). By contrast, we find a positive concave relationship without occupation indicators, as column (4) shows. It peaks as the graduate share nears 64 percent. The standardized effect is 0.034 (12.8 percent of a standard deviation). These estimates are again consistent with the two main predictions of our model: a substitution effect away from cognitive tasks at the worker level and an aggregate composition effect toward cognitive tasks.

Columns (5) and (6) examine social tasks. Unlike the routine or the cognitive, social tasks are not part of our model. We analyze them nonetheless for completeness. Our estimates are broadly similar to the regressions of the cognitive score. If we include occupation indicators, we find a negative impact of an increase in the graduate share on social tasks. The quadratic term is especially salient. The standardized effect is –0.014 (3.4 percent of a standard deviation). Should we exclude occupation indicators, the response function becomes positive and concave. The maximum occurs when graduates represent 54 percent of employed workers. The standardized effect is 0.053 (13.1 percent of a standard deviation).

The last two columns show regressions for the ratio of the routine score to the sum of task scores. Hence, the resulting coefficients combine the individual effects in columns (1) through (6). They are consistent with the regressions of the routine score in the first two

18 For comparison, the Bartik instrument implies that the effect of an increase in the graduate share on routine tasks peaks when the graduate share nears 26.5 percent and turns negative when it reaches 53 percent. The implied standardized effect is 0.005 (1.7 percent of a standard deviation).

columns. The most noticeable difference is that the coefficient on the square of the graduate is not significant when occupation indicators are included.

6.2. The impact of task assignment on wages and hours

Table 6 shows linear regressions of hourly wages, monthly wages and an indicator of part-time work on task indexes. As Autor and Handel (2013) argue, the resulting coefficients are not causal, since task assignments may depend on workers' comparative advantages. Like Autor and Handel (2013), we present these estimates nevertheless in an effort to provide empirical evidence for future research. Note that wage regressions do not use data from the 2013 WCS because it did not collect comparable information.

The first two columns consider hourly wages. Differences in job content between occupations seem important, since coefficients are sensitive to the addition of occupation indicators. However, we find significant correlations within occupations as well. Routine and cognitive tasks have opposite effects on pay: routine tasks decrease wages, whereas cognitive tasks raise them. If we include occupation indicators, hourly wages fall by 0.44 percent for an increase of one standard deviation in the routine score and rise by 1.57 percent for an equivalent increase in the cognitive score. If we do not, the corresponding estimates are 2.10 and 3.92 percent. The role of social tasks is less clear: with occupation controls, we find that hourly wages fall by 0.44 percent for a shift of one standard deviation in the social score; without them, hourly wages rise by 0.52 percent.

Columns (3) and (4) examine monthly wages. We restrict the sample to full-time workers. The coefficients on routine tasks are close to those for hourly wages. The coefficients on cognitive tasks are slightly larger. We see more change for social tasks: with occupation controls, monthly wages rise by 0.48 percent for a shift of one standard deviation in the social score; without them, by 1.66 percent. Note that these effects have the same sign, which was not the case for hourly wages.

Columns (5) and (6) show estimates for an indicator of part-time contract (hence, a linear probability model). We analyze part-time status instead of hours because we do not observe hours for all observations. We find that all three indexes are negatively associated with part-time work. This result is particularly clear for routine tasks. These estimates admit a simple explanation: part-time workers may perform fewer tasks in any category because they spend less time at work.

Our wage regressions are consistent with Autor and Handel's (2013). The authors classify tasks into three groups: abstract, routine and manual. (Their abstract tasks correspond to our cognitive. They do not discuss social tasks.) They study the impact of job content on wages within occupations with survey data from the United States. Although they examine a different labor market and measure job content through different variables, their coefficients are surprisingly similar to ours in direction and magnitude. Albeit exploratory, our analyses should provide useful guidance for future research on task assignment.

TABLE 6: IMPACT OF JOB CONTENT ON WAGES AND HOURS

	Log hourly wages		Log monthly wages		Part time	
	(1)	(2)	(3)	(4)	(5)	(6)
Routine tasks	–0.014***	–0.068***	–0.016***	–0.077***	–0.017***	–0.047***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Cognitive tasks	0.059***	0.146***	0.083***	0.181***	–0.004	–0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Social tasks	–0.011***	0.013***	0.012***	0.041***	–0.022***	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Controls						
Individual characteristics	11	11	10	10	10	10
Education fixed effects	4	4	4	4	4	4
Occupation fixed effects	22		22		22	
Region fixed effects	20	20	20	20	20	20
Year fixed effects	3	3	3	3	4	4
Fit						
Sample	All	All	Full time	Full time	All	All
Years	1991–2005	1991–2005	1991–2005	1991–2005	1991–2013	1991–2013
Observations	67,019	67,019	57,488	57,488	94,253	94,253
Parameters	63	63	62	62	63	63
Mean outcome	2.444	2.444	7.482	7.482	0.165	0.165
Adjusted R^2	0.599	0.522	0.625	0.484	0.209	0.173

Notes: The table shows coefficients from ordinary linear regressions. Standard errors (in parentheses) are robust to heteroscedasticity. See Section 2 for a description of the task indexes. *Legend:* Stars denote significance: *, at the 10 percent level; **, 5 percent; ***, 1 percent.

7. Conclusion

This paper contributes to a growing literature about task assignment. Since the seminal work of Autor, Levy and Murnane (2003), this research has provided insight into employment polarization, wage inequality and much else. It has mostly studied the influence of job content on an outcome of interest. We take the opposite approach and investigate the determination of job content in equilibrium. In particular, we show that the skill supply affects job content by analyzing the impact of an increase in the share of university graduates in the French workforce from 18 percent in 1991 to 36 percent in 2013. We find that higher average educational attainment is associated with more routine, fewer cognitive and fewer social tasks within occupations and with fewer routine, more cognitive and more social tasks across occupations.

Our results have three methodological implications for future research. First, researchers should explore variation in job content within occupations in greater depth. Second, occupations evolve, so care is needed in analyzing long-term trends in labor markets on the basis of rigid occupational classifications. Third, identification deserves attention as task assignment is endogenous to both worker aptitudes and aggregate conditions.

Our approach has a significant limitation: although we can measure changes in task assignment at the individual level, we can not distinguish the intensive margin (i.e. changes in tasks for a given worker in a given job) and the extensive margin (i.e. changes through job creation, job destruction and employee turnover). Panel data would help us address this shortcoming. It would also help us study the influence of task assignment on workers' careers, wage inequality and more – a promising avenue for future research.

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Appendix A. Additional results

Table 7 shows our main results for the Bartik instrument. Our qualitative results are robust (cf. Table 5). For instance, the Bartik instrument also implies that the effect of an increase in the graduate share on routine tasks is concave. It peaks when the graduate share nears 26.5 percent (against 32 percent for the retirement instrument) and turns negative when it reaches 53 percent (against 64 percent). The standardized effect is 0.005 (against 0.014).

TABLE 7: IMPACT OF CHANGES IN THE GRADUATE SHARE ON TASK ASSIGNMENT (BARTIK INSTRUMENT)

	Routine tasks		Cognitive tasks		Social tasks		Routine tasks (share)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bartik instrument								
Share of university graduates	0.162**	−0.698***	−0.203***	0.480***	−0.036	0.906***	0.112***	−0.702***
by occupation, region and year	(0.072)	(0.017)	(0.063)	(0.015)	(0.093)	(0.024)	(0.050)	(0.013)
Squared share of university graduates	−0.306***	0.552***	−0.135*	−0.375***	−0.305***	−0.855***	−0.049	0.596***
by occupation, region and year	(0.068)	(0.019)	(0.070)	(0.018)	(0.106)	(0.028)	(0.049)	(0.014)
No instrument								
Share of university graduates	0.108**	−0.667***	−0.103**	0.458***	−0.044	0.871***	0.067**	−0.670***
by occupation, region and year	(0.045)	(0.016)	(0.040)	(0.014)	(0.058)	(0.022)	(0.030)	(0.012)
Squared share of university graduates	−0.164***	0.521***	−0.021	−0.350***	−0.225***	−0.824***	−0.029	0.563***
by occupation, region and year	(0.040)	(0.018)	(0.040)	(0.017)	(0.059)	(0.025)	(0.027)	(0.013)
Controls								
Individual characteristics	11	11	11	11	11	11	11	11
Education fixed effects	4	4	4	4	4	4	4	4
Occupation fixed effects	22		22		22		22	
Region fixed effects	20	20	20	20	20	20	20	20
Year fixed effects	4	4	4	4	4	4	4	4
Fit								
Observations	94,253	94,253	94,253	94,253	94,253	94,253	93,592	93,592
Parameters	63	41	63	41	63	41	63	41
Adjusted R^2 (OLS)	0.223	0.150	0.156	0.117	0.194	0.086	0.305	0.178

Notes: Standard errors (in parentheses) are robust to heteroscedasticity. The share of routine tasks is the ratio of routine tasks to the sum of task indexes. See Section 2 for a description of the task indexes. The instrument is a projection of the share of graduates by birth region and occupation (q.v. Section 5). It supposes that the contingents of graduates and nongraduates will evolve at the national rate in each local labor market between surveys. *Legend:* Stars denote significance: *, at the 10 percent level; **, 5 percent; ***, 1 percent.