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EERI Research Paper Series No 08/2002

ISSN: 2031-4892

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Striking Features of the Portuguese Labor Market

William H. Greene[†] *and Ana P. Martins*[*]

Abstract: It is the purpose of this research to present some evidence on the factors explaining the observed industry differences in incidence and duration of Portuguese strikes. The analysis relies on the proposal of adverse-selection and moral hazard arguments to (partly) explain strikes, interpreting these as costs incurred by more productive workers to signal their potential. Separating equilibrium with strikes were advanced, possible if more productive workers have stronger relative preferences for income relative to leisure than less productive workers. Empirical consequences of such models were inquired. The availability of mean sector data for strike incidence and severeness required the modeling of binary choice frameworks and adapt sample selection algorithms to use the zero observations. If traditional arguments based on institutional arrangements such as unionization, economic profits, proxied by industry concentration, and in general asymmetric information, associated with larger firms, were found important to explain strike activity, some evidence was also encountered on the relevance of time schedules and part-time usage indicators in strike incidence and severeness regressions. Relative wage differentials (with respect to wage regressions expectations) were also found important, as well as industry dynamism – affecting strike activity negatively (supporting countercyclical strike occurrences), effect reinforced by sector labor productivity. Substitution for intermediate products would seem to promote labor disputes.

JEL: J52, J41, D82, C24, C25
Keywords: Strikes, Asymmetric Information, Signaling, Labor Contracts, Part-Time Work; Mean or Grouped Data and Limited Dependent Variables, Binary Choice Models with Mean or Grouped Data; Sample Selection with Mean Data.

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Striking Features of the Portuguese Labor Market

Introduction

Strikes were prohibited by Portuguese law for decades before 1974, and information about their extension was not (we believe) immediately recorded in official statistical sources. As far as we know, there are no studies that inquire similarities of behavior to equivalent international occurrences. The aim of this research is twofold: on the one hand, we propose some simple theoretical developments of asymmetrical informational models that allow us to understand the individual´s willingness to participate in a strike. On the other, we assess the impact of a broad range of variables on a cross-section of industry strike inflictions.

A(n economic or classical, as opposed to sympathy/etic and or political) strike is a "organized work stoppage carried out by a group of employees, for the purpose either of enforcing demands relating to employment conditions on their employer or of protesting unfair labor practices" [1]. Several elements can be related to strikes. One is their determinants: why and when it occurs and for how long it lasts. A second matter is the measure and definition of the extent of its (un)successfulness and causes of such outcomes. A third issue is the relation to unions, union structure and formation and pertaining institutional arrangements. Finally, what is the general and relative significance of the whole process and corresponding outcome – the positioning in an economic theory or framework.

The literature on strikes relevant to this analysis comes from two different lines. One is connected to the formal or analytical explanation of the apparently inefficient strike phenomena, the "Hicks paradox"; the argument can be explained as follows: if we knew where it is going to end up, we could get there immediately and avoid the cost of the strike (unless we include "taste for destruction" of either side, a not novel argument: the "pleasure of striking" may reflect aggressiveness in attitudes of workers and employers [2] - gratuitous violence, even if not rational, does exist [3]... After all, we consider rational what

[1] Online Encarta Encyclopedia.

[2] See Reder and Neuman (1980), p. 885. They capture differences in the implied strike propensities in the disturbances, though... Kaufman (1982) cites the importance of psychological or attitudinal factors, such as worker militancy, public opinion climate – but admits the difficulty in their measurement.

[3] It is commonly found in childhood and adolescence... Exploited (diverted?...) by computer games industry.

leads to good results – even envy can be "rational" if put to good use in the establishment of standards for human advancement and achievement. Or admit it as a substitute for lethargic work careers in large impersonal organizations.) [4]. The second line is empirical, having dealt with the study of both strike determinants and settlement outcomes – even if not simultaneously. Some interaction has occurred between the two, and inspection of implications of theoretical models is a common feature of most articles on strike activity.

There are several "rational" reasons why strikes can occur: one is uncertainty and imperfect/asymmetric information – see related surveys in Kennan and Wilson (1990), Kreps and Sobel (1994) and Riley (2001) - and/or imperfect foresight of the players. Another, implicitly or explicitly explored in the literature, is imperfect institutional arrangements – translated sometimes in faulty or sluggish (e.g., requiring delays or suffering other real world "attrition") "rules of the game". And we can think of discontinuities, indivisibilities, representation of heterogeneous workers, finiteness of agents lives or even time discreetness, some addressed in the bargaining literature, as leading to additional and similar explanations.

Imperfect information, in particular, reputation establishment was the driving mechanism in the early Ashenfelter and Johnson´s (1969) modelling. Theirs is a political model of organization rationale involving union leaders-rank and file relations and relies on the ad-hoc formalization of a union´s wage concession curve, negatively related to strike duration; union leader – rank relations may be consistent with the opposite pattern found (below) for the relation between aggregate strike incidence and strikers response to the business cycle.

Historically, a joint or total cost foundation for the determinants of strikes is attributed to Kennan (1980) and Reder and Neuman (1980) – protocols would be devised to minimize aggregate strike costs; the higher total costs of strikes, (inversely related to "ease of intertemporal substitution of production" through storage, i.e., inventories [5]; those costs would be lower in durable goods markets relative to others) the lower strike incidence. But there was no formal game forwarded.

Asymmetric information and uncertainty is pointed out on the work by Mauro (1982) and Kaufman (1982), which find divergent expectations with respect to inflation as influencing strikes. But formally, their inclusion is only done in later models.

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[4] Interestingly, Hicks conclusion was somewhat recaptured in Rubinstein´s (1982) sequential bargaining model – where a division of the pie is achieved with no delay at the beginning of the game.

[5] Even if these can also be inversely related to the business cycle – see also Byrne and King (1986).

Hayes (1984) advances models of union-monopoly firm bargaining with asymmetric information over states of nature, a one-contract framework (no commitment involved). Later on, the division of a "cake" and opportunity costs of delay imposed by strikes are expressed in non-cooperative multiperiod bargaining structures like Tracy´s (1987) recursive learning model, for example, and Hart (1989). These authors present strikes as screening devices by which the union learns the firm´s profitability, a random variable, the effective occurrence of which is imperfectly perceived by the union. Other models can be found in the strategic bargaining literature, surveyed in Kennan and Wilson (1990) and, especially (1993) and Manzini (1998). Kennan and Wilson distinguish those screening models, where the union gives the cards – i.e., either makes the offers, is the leader of a two-sided game, effects price discrimination - from signalling structures [6], such as Admati and Perry´s (1987), where the firm, which chooses the delay, just signals its low profitability by not accepting the first (high wage) offer; and from war of attrition games – in which both players can make offers, there is an explicit cost of delay for each party rather than discounting, and the result is a "see who yields later" and, usually, a "winner takes all" type of splitting outcome [7]. The first two classes of models are (usually) one-sided private information games and strikes/delays occur in the low state only [8]. Procyclicity is explained in some of all set of models, through the impact of an increase in the probability of observing high states for example [9], but not in most (Tracy, 1987 for example [10]). They generate similar implications as Ashenfelter and Johnston – namely, a negatively sloped concession schedule (screening and signalling models imply declining settlement rates with strike duration) [11]; of the three classes, Kennan and Wilson (1989) and (1993) conclude that signalling models seem more inadequate in view of the evidence.

[6] See also Riley (2001) for the modern distinction of the understanding of the two concepts. Kreps and Sobel (1994) identify screening models as those where "the uninformed party has the leading role in setting the terms of the contract", otherwise, signalling is in effect; for them, if the informed party has all the bargaining power, he may extract all the surplus, and the game assumes what they term a "take-it-or-leave-it" formulation, which they distinguish from other signalling situations.

[7] This is also Rubinstein´s perfect information outcome when costs of delay of the two plays differ, with the party with lower costs receiving all the surplus if he is the first mover.

[8] Riley (2001), p. 467, footnote 28, points to the fact that including asymmetry in war of attrition models could yield high-profit firms enduring more strikes, though.

[9] See Harrison and Stewart (1994), p. 527.

[10] He assumes changes in expected rents leaving "uncertainty unchanged" – then, strikes diminish with total expected rents. The opposite pattern is found in Booth and Cressy (1990) two period model: they conclude that "strike probabilities increase with the surplus to be bargained over".

[11] Roles of union and firm are somehow reversed (at least) in screening models relative to Ashenfelter and Johnston, however: given the resistance curve, the firm acts as a "leader" in their framework.

Uncertainty should increase strikes according to most theories [12], as well as the discount factor [13].

More recently, outside options to the parties have entered the scene [14] – namely, the so-called "holdout threat" of Fernandez and Glazer (1991), Haller and Holden (1990), Cramton and Tracy (1992 and 1994), Gu and Kuhn (1998) [15]: the possibility of postponing strike initiation while keeping the/a previous (contract) wage level. Some older models implicitly included the possibility of some income or utility accruing to union members during a strike – that is the case of Booth and Cressy (1990), Card (1990b) and others; the novelty is a third option. The first consequence of the outside alternative – and of a flow of mana rather than a fixed pie [16] - is that, even without uncertainty, the Rubinstein immediate settlement result breaks down; moreover, it usually generates multiplicity of equilibria.

The effect of institutional arrangements such as bargaining structure, is also being devoted some attention – studies such as Cheung and Davidson (1991) and Kuhn and Gu (1998) analyse multifirm bargaining and how alternative bargaining protocols may affect strike occurrence. And industry structure, such as monopoly (oligopoly) power [17], market share [18]; and features of production technologies required by product characteristics: product durability and inventories [19].

The empirical literature on strikes is also vast. We can distinguish two broad questions: the determinants of strikes, and the effects of strikes on wages. The second type of questions is sometimes concerned with the union´s concession schedule of Ashenfelter and Johnson (1969), and the implied negative relation that should be found between wages and strikes if asymmetric information models in which the union screens the firm [20] such as Hayes (1984) or Hart (1989) imply were appropriate: it includes studies such as

[12] Booth and Cressy (1990) find an ambiguous effect of the dispersion in profitability, though.

[13] Hart (1989), Booth and Cressy (1990). In these, the discount factor is common to both union and the firm. Consistently, in Ashenfelter and Johnson (1969), strike length decreases with the firm's interest rate.

[14] Shaked and Sutton (1984) extend Rubinstein model allowing replacement of workers by the firm – yet, the immediate settlement result is recovered.

[15] In these authors´ model, holdouts finance delays and learning by the union of other settlements in the industry.

[16] See Manzini (1998), p. 10 and 12.

[17] Feuss (1990). He also analyses firm size.

[18] Clark (1996) presents a scenario where market share affects future profitability; also Hart (1989).

[19] Clark (1997), Leach (1997), picking up Reder and Neuman (1980).

[20] Such negative relation occurs for a setting where the firm has some information inadequately perceived by the union. Interestingly, if we reverse the roles, as noted by McConnell (1989), p. 803, and "the *union* possesses information not shared by the firm, and the work stoppage is used by the firm as a screening device then there would be a *positive* correlation between wages and strikes." This point is also made in Hart (1989), who concludes that reversing roles seems an interesting avenue of research.

McConnell (1989), Card (1990b), Jimenez-Martin (1999). We shall not be dealing with this issue; rather we will be more interested in explaining inter-industry differences in strike occurrences, the first line of questions. In these other studies, surveyed in Card (1990a), there seemed to be a focus on the response of strikes to the business cycle [21]: strike incidence seems procyclical [22], duration counter-cyclical; seasonality is sometimes contemplated [23]. Uncertainty may promote strikes [24]. Firm size has a positive effect on the dispute rates [25], industry concentration has mixed elements [26]; production technology seems to be relevant in some cases [27]. Higher wages at end of a previous contract diminishes strikes; previous strike experience seems to deter strike occurrence [28]. Bargaining structure indicators are sometimes included [29]. Less often, workforce characteristics like education and age – Tracy (1986) – experience and tenure – Tracy (1987) –, proportion of skilled labor force – Booth and Cressy (1990) – and of manual workers – Ingram, Metcalf and Wadsworth (1993) - are controlled for; and management practices such as existence of evaluation schemes [30] and employers´ striker replacement

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[21] More recent explorations include Harrison and Stewart (1994) for Canada; Reilly (1996) for Ireland. These studies conclude for procyclicity. Ingram, Metcalf and Wadsworth (1993) report countercyclical strikes for British manufacturing.

[22] Even if opposite patterns are sometimes found when both state and industry cycle indicators are included in regressions – see Tracy (1986), for example: procyclicity would be related to local labor market conditions. Cramton and Tracy (1994) conclude that "tight aggregate and industry labor market conditions shift the composition of disputes towards strikes" (they analyse holdouts as well).

[23] From Vroman (1989), in Canada, the last quarter of the year (Autumn) would be a period of higher strike incidence, the second quarter (Spring) of low strikes. Yet, such pattern may just reflect contract endings and/or initiations. For the US, Tracy (1986) finds small monthly variations for the US, with June being above average (or rather, above October) and December below; Card (1988) also inspects the subject. (Both authors control for other factors.)

[24] Stock price, for example: see Cramton and Tracy (1994).

[25] See Gunderson, Kervin and Reid (1986) for Canada; Cramton and Tracy (1994) for the US; Ingram, Metcalf and Wadsworth (1993), Booth and Cressy (1990, establishment size) for Britain. Other studies did not find the same sign effect – Tracy (1986), for example.

[26] Tracy (1986), Cramton and Tracy (1994) report positive effects on incidence – negative for duration in Tracy (1987) - for the US; yet, according to Goddard (1992), market share decreases strike incidence in Canada.

[27] Ingram, Metcalf and Wadsworth (1993) consider share of labor costs (negative impact on strikes), and Tracy´s studies include capital-labor ratios (positive impact, but not always; usually, statistically insignificant).

[28] Even if evidence on state dependence displayed by strike incidence (the "teetotal" versus the "narcotic" effect of previous strike episodes controversy) is vague and inconsistent – see Clark (1996) for a recent survey; Schnell and Gramm (1987) that support the teetotaler effect, and Card (1988).

[29] Union membership concentration seems to decrease strikes, at least in the seventies – Cramton and Tracy (1994). Union coverage - Tracy (1986) – induces strikes (US). For British manufacturing, multiunionism (multiple unions with the right to bargain) increases strikes, according to Ingram, Metcalf and Wadsworth (1993).

[30] Booth and Cressy (1990) find a positive effect on strike probabilities for British data.

strategies [31]. Foreign openness is also considered [32]. Holdout – strike differences in disputes have been addressed in the 90´s [33].

From the reading of the modern literature, three main considerations arise:

Firstly, there is, in general, no reference to workers effective productivity or labor contribution to the "pie" [34]. In some, the size of the pie is fixed [35] – only delays in its availability affect the parties well-being. In almost all, the positive influence on output prices of work stoppages is neglected [36]: they are positive, not normative studies. Social welfare statements are absent. The policy implication one generally infers is that under competitive output and labor markets, strikes should be prohibited by law [37] – immediate replacement of strikers allowed, or compulsory arbitration in case of disagreement enforced - as they denote an uncompetitive monopoly practice, possibly, the use of an employment strategy – labor rationing – in order to increase the wage rate. Indeed, a lot of policies were devised and implemented to diminish strikes, some more effective than others – see Kaufman (1982) for the US – also analysing political factors; Gunderson, Kervin and Reid (1989), Gunderson and Melino (1990) for Canada; Ingram, Metcalf and Wadsworth (1993) using data for British manufacturing; Hutchens, Lipsky and Stern (1992) research the impact of unemployment benefit allowances for strikers in the US [38]; Goerke (1998)

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[31] Schnell and Gramm (1993) find a positive impact on strike duration, attributed to a lower total cost of strikes. They provide a survey of related literature.

[32] Cramton and Tracy (1994) for the US use import penetration ratios – they find insignificant effects. Budd (1994) analyses multinationals for Canada and the presence of international unions; it would seem that differentiated country affiliation of unions would imply an effect on strike behavior.

[33] Cramton and Tracy (1992 and 1994) for the US, Gu and Kuhn (1998) for Canada.

[34] Behavioral (sociological) theories – see Godard (1992) for an illustration – describe strikes as a collective expression of worker discontent with what the workers feel unfair towards them as a group, admitting quitting as the rational alternative. In bargaining models, at most there is an alternative wage - union or union members reservation payoffs or outside opportunities are included in Tracy (1987), for example, increasing strike probabilities; Card (1990b) admits an alternative wage during a strike, having the same effect.

[35] Indeed under the standard competitive firm´s labor demand diagram, the surplus or total rent is maximized at the employment level for which demand equals supply – whether the firm is a monopsonist in the labor market, or not and supply is infinitely elastic at the market wage. One could argue that it is the total surplus that is to be bargained over – with competitive input markets (including other inputs), only if the firm is generating abnormal profits can the wage rise above equilibrium.

[36] Even if some studies have addressed the impact of strikes on shareholders of struck and nonstruck competitors – see Kramer and Vasconcellos (1996), for a recent example, but restricted to some highly concentrated industries, where only slight effects were found. Such possibility clearly underlies Carter *et a*l (1987) and Feuss´s (1990) theoretical analysis - implicitly reminding that unsuccessful general strikes may actually improve the firms´ profitability - but they are of the few.

[37] Even if it has been argued that in asymmetric models where the union screens the true state of the firm, strikes can be *ex ante* Pareto optimal - Jimenez-Martin (1999), p. 586 – or an "*ex ante* efficient bargaining tool" - Ingram, Metcalf and Wadsworth (1993). In general, a discussion of the welfare value of signalling can be found in Stiglitz (1975) – when matching, chain production and self-motivation are present, a separating equilibrium can be Pareto improving.

[38] If the employer could continue to operate at normal level, the strikers could collect the benefit.

inspects (theoretically) and surveys the effect of taxes, an eventual redistributive substitute, on strike activity. But prohibition is not common in democratic societies.

Secondly, a neglected aspect of strike activity is the purposefulness of reducing labor supply - constrained by standard hours contracts - by workers at the current wage level. One of the different features of strikes relative to other wars is that, rather than actual losses or destruction [39], they involve the obstruction to income gains – that is, they imply income opportunity losses, usually transmitted as delays to production, akin to haggling costs. Rather than destroy property, strikes waste time, production time. To the extent that time has alternative usages to work, a stay-at-home strike may yield some utility in the form of leisure and have similar causes and consequences to absenteeism [40]. On the other hand, it involves costs – either money (as union fees) or time (picketing or other) - which are born individually by workers. Yet, none of the two cited branches of literature embodies concerns or outcomes of labor contract bargaining related to the settlement of the standard workweek.

Finally, the empirical literature, for the U.S. and Canada, has focussed on frequency, incidence, size, and duration. Most, if not all, however, do not consider it – mostly due, we believe, to unavailable information – an individual (worker) occurrence. That is, figures are associated to groups rather than to elements, or workers involved; "size" is related to rank and file heterogeneity and to dispersion in the union´s or union members utility and measured by total number of strikers, with no reference to total employment [41]. For instance, usual observations – or weights - are number of contracts surveyed, not number of workers or aggregate days lost: strike duration is defined over strikers only, not as days lost per worker employed [42]. This may be a correct point of view if one is analysing union-firm institutional negotiations, theoretically founded on current bargaining models, where the "pie" is negotiated between and shared by two players, equally motivated towards income gain and with differentiated strength based only in potential differences in impatience or rules of protocol; and, usually, strikes do not involve an individual only but a reference set with common working status of some sort. However,

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39 Even if the main difference may come from the fact that they do not destroy lives, or number of agents contributing to and sharing the pie on each side.

40 Booth and Cressy (1990) include a leisure value of the strike to the union in a two period model, for example, which also accommodates the existence of strike funds; a fractioning of work-time, however, is not explicitly accomplished.

41 See Harrison and Stewart (1993) inspecting the impact of strike size on duration.

42 Even if strike duration measures days lost per striker. Still, weighting by some indicator of involved workers is absent in general. This problem can be related to the distinction between the propensity to strike and the opportunity to strike discussed by Kaufman (1982), associating the later to union membership.

it does not seem to properly account for wildcat strikes – according to Byrne and King (1986), more than 20% of work stoppages in the U.S. manufacturing between 1960 and 1977 –, or the small response of workers to the call for some strikes by the unions. Nor is it sufficient if we want to focus on the aggregate, per capita, or per worker, discontent or losses of negotiation breakdowns. Moreover, indicators that mirror these concerns may be more appropriate to proceed with international and industry comparisons.

Hence, our theoretical work tries to begin the discussion of the three issues, relying on the familiar consumer-worker problem. We admit imperfect information scenarios in which heterogeneous workers´ productivity is not observable by the firm. Firstly, we analyse the possibilities available for a firm that can monitor hours – we recover in some cases the Rothschild and Stiglitz (1976) non-linear pricing type of separating solution. On one (second) model – or rather, framework -, strike is introduced as a friction in an imperfect information world with labor contracts and with subjective costs of a job change. On another, as an individual signal of high productivity workers a la Spence (1973) when hours cannot be constrained in the contract; uniform workweeks imposed by hours monitoring problems are finally introduced. Signalling models have had many applications in labor markets: returns and choice of education or credentials, Wolpin (1977), Riley (1979), Weiss (1983) and, of course, Spence (1973) are early references, Wilson (1988); layoffs patterns, Waldman (1984), Greenwald (1986), Gibbons and Katz (1991); unemployment self-selection of higher qualified workers was studied by McCormick (1990) and Ma and Weiss (1993). That strikes, involving costs, may, thus, have a role as an individual signal seems somehow reasonable and subscribes to this literature; their effective role as a signal, however, is going to require that more productive workers have a stronger relative preference for income relative to leisure.

Empirically, we proceed by inspecting frequency and duration equations in which the dependent variable is normalized to the total extent of the industry.

The analysis proceeds as follows: in section 1, we present some international regularities in strike occurrences and trends in Portuguese strike behavior. Section 2, forwards two simple signalling model of strikes. The empirical evidence on industry incidence and duration is exposed in section 3 to 5: section 3 uses weighted least squares procedures; sections 4 and 5 apply limited dependent variable techniques to explain strike frequency and average time loss respectively. The analysis resumes in section 6 with a brief summary.

1. Regularities in Strikes Data

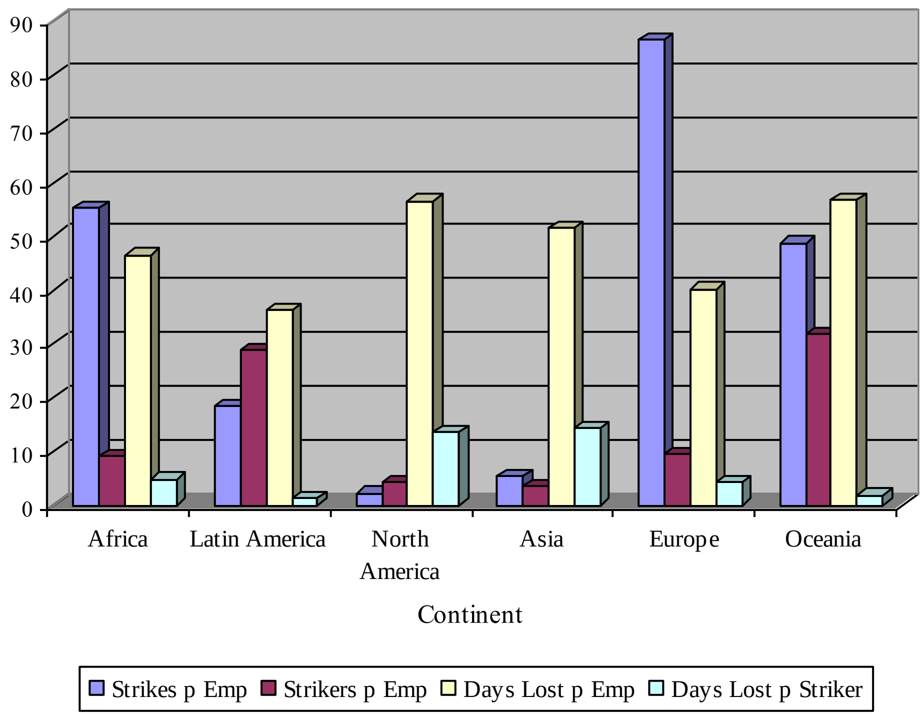
1.1. Labor Disputes in the World Economy

Labor disputes have remarkably decreased over the last decade, an eventual outcome of overall improvement in earnings and productivity in the world economies. We present below some indicators on the international distribution pattern of labor disputes, the main source of which is the Yearbook of Labor Statistics from the International Labor Office. Part of the data includes all labor disputes, i.e., both strikes and lockouts. We constructed, for 1997 (1996 or 1995 when only available) Strikes per Employment, Workers Involved per Total Employment and Days Lost per Total Employment and Days Lost per Striker (medium strike length); the third indicator was reported for 20 countries and also used below; the others were collected for around 80 countries. Data was aggregated according to three criteria – firstly, by Continent, presented in Graph 1; secondly by the distinction of the IMF between industrialized and non-industrialized countries – Graph 2, where the EEC block was represented, along with some industrialized nations and Portugal. Finally – Graph 3 -, according to the UN – in PNUD (1999) - classification of degree of human development. Strikes per employment is an unusual, perhaps least significant, indicator – expected to be inversely related to firm size among the nations being compared; yet, it is the purpose of the ratio to control for country size.

By continent, strikers per Employed persons seem to be higher in Oceania and Latin America; lower in Asia and North America. Non-industrialized countries seem to be more affected than industrialized ones, but the European Community shows higher rates than both blocks. US and Japan do not indicate a high proportion of workers on strike.

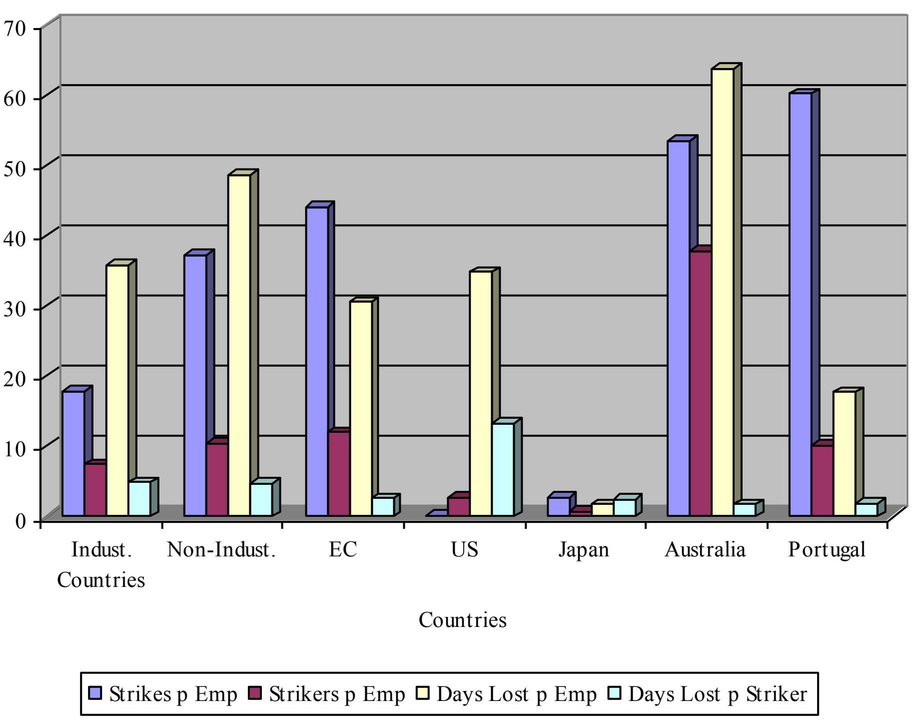
Days lost per Employed persons show a different pattern: they are higher in North America, Oceania and Asia; lower in Latin America and Europe. Non-industrialized countries are, again, more affected than industrialized economies, and the European Community shows now lower rates of days lost than both blocks. Data for the US using the ratio of days lost to employment may be upward biased, but the country exhibits very high work time losses per employed worker due to strikes; Japan has very low labor disputes, and Portugal also shows low levels.

In general, medium human developed countries show higher strike incidence than highly developed economies; yet countries with low development have almost no strikes – in our data, this block is underrepresented; yet, it would seem that strike organization would require the crossing of some development threshold – an hypothesis consistent with the history of strikes, which emerge with industrialization.

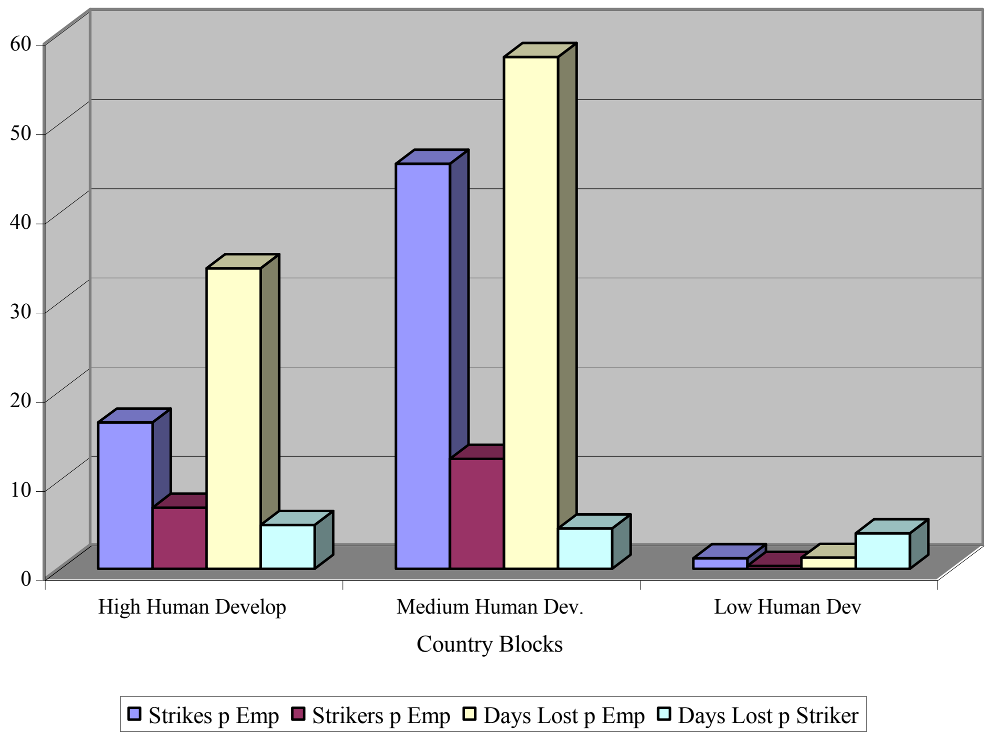


Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 1



Graph 2



Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 3

It is thus not clear from the pictures above whether strikes increase or decrease with development level. We present in Table 1 the correlations between the several indicators and also with per capita Gross National Product (US dollars) and the United Nations ranking of human development for 1997.

Except for strike length, most indicators are positively correlated among themselves. Countries with higher strike activity by those other criteria would have strikes of lower average length.

Apparently, strike incidence and severeness move in opposite direction to human development and income, even if correlations are not always significant. This pattern is specially significant in Days Lost per Worker Employed directly reported in the statistics, which covers only a sub-sample of 20 countries, in general, more developed economies: possibly re-instating the hypothesis that even if well-being decreases strike incidence, some level of economic organization must be achieved for strikes to work in this fashion.

1997	Strikes per Employm.	Strikers per Employment	Days Lost per Employment	Days Lost per Employment-2	Days Lost per Striker	PNB per capita (US dollars)	Rank HDI
Strikers per Employment	0.202 ** (79)	1					
Days Lost per Employment	0.238 * (77)	0.339 * (76)	1				
Days Lost per Employment -2	0.803 * (19)	0.753 * (20)	0.896 * (20)	1			
Days Lost per Striker	-0.123 (68)	-0.358 * (69)	0.163 (69)	-0.258 (20)	1		
PNB per capita (US dollars)	-0.146 (86)	-0.142 (80)	-0.136 (78)	-0.698 * (20)	-0.202** (69)	1	
Rank HDI	0.0283 (82)	0.0454 (76)	0.150 (74)	0.708 * (20)	0.278 * (65)	-0.847 * (83)	1
Mean [std. dev.]	0.03070 [0.071865] (86)	9.24 [16.21] (80)	43.73 [103.73] (78)	33.37 [50.82] (20)	9.51 [8.40] (69)	11002 [12914] (86)	62.42 [49.71] (83)

Table 1

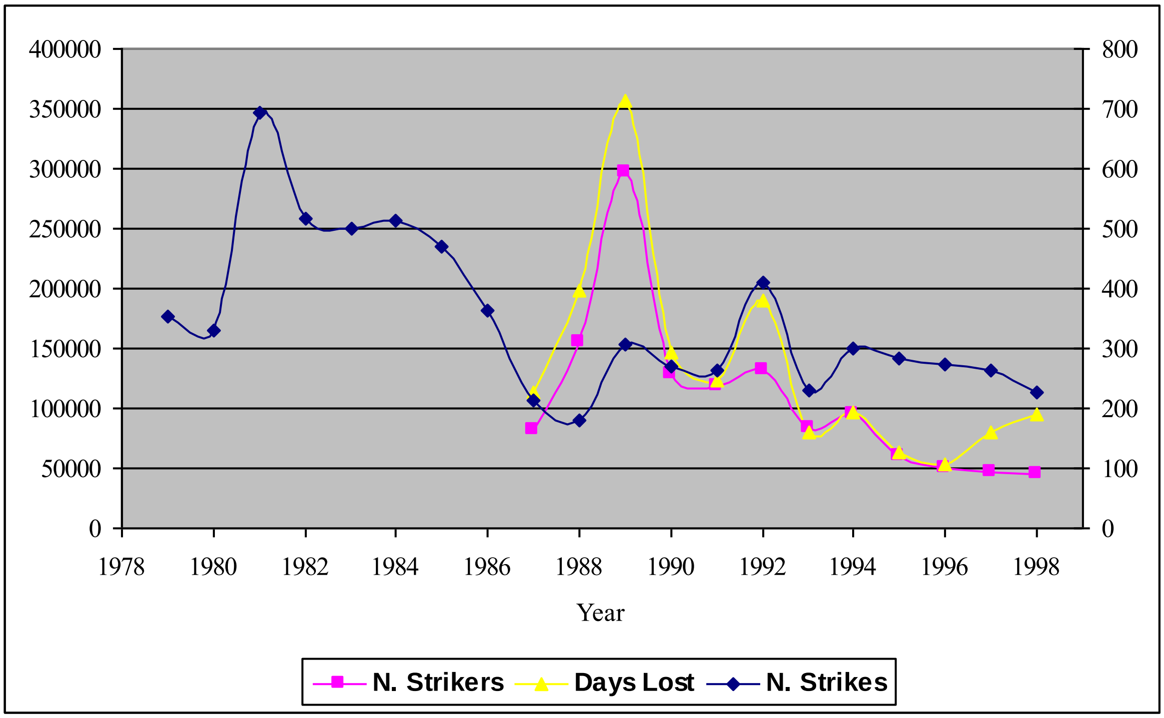
Notes: 1. Per Employment indicators are defined per a thousand employed persons. Strikes per Employment, Strikers per Employment, and Days Lost per Employment were, in fact, constructed from total labor disputes – strikes and lockouts - over employment (Labor Force in some cases). Days Lost per Employment-2 is reported in Yearbook of Labour Statistics.
2. Correlations and means are weighted by Total Employment.
3. Number of observations in parenthesis.

1.2. Recent Statistical History of Portuguese Strikes.

1. Strikes evolution in Portugal may be considered to present two main periods: 1974-1983 and 1984 onwards. In the first phase, coinciding with major social upheaval, labor conflicts were at a much higher levels - possibly reflecting repressed accumulated discontent, and/or politically driven or supported economic disruption. The second phase exhibits much milder outbreaks, suggesting a general improvement in economic and wage conditions - or a decrease in prospects of successful bargaining resulting from striking.

We present in Graph 4 the recent evolution of three absolute indicators of strike activity in Portugal – number of classic strikes, N. Strikes, number of workers involved, N.

Strikers, and total days lost due to strike motives, Days Lost [43]. After 1986, 1989 and 1992 were years of high disputes [44], but workers and days lost have in general dropped till the end on the sampled period (days lost increased a little bit in the last two years); number of strike occurrences remained relatively stable in the last decade (maybe with the exception of 1992).



Graph 4

Graph 5 reports the evolution of some macroeconomic indicators [45]: Total Employment growth rate, Real GDP per capita growth rate, the growth rate of Real Wages per Worker (deflated by the private consumption deflator) and the Unemployment Rate (the latter scaled in the secondary or right axis). If during the eighties the unemployment rate seems to have moved inversely to the other indicators, after 1992, the pattern is not so clear.

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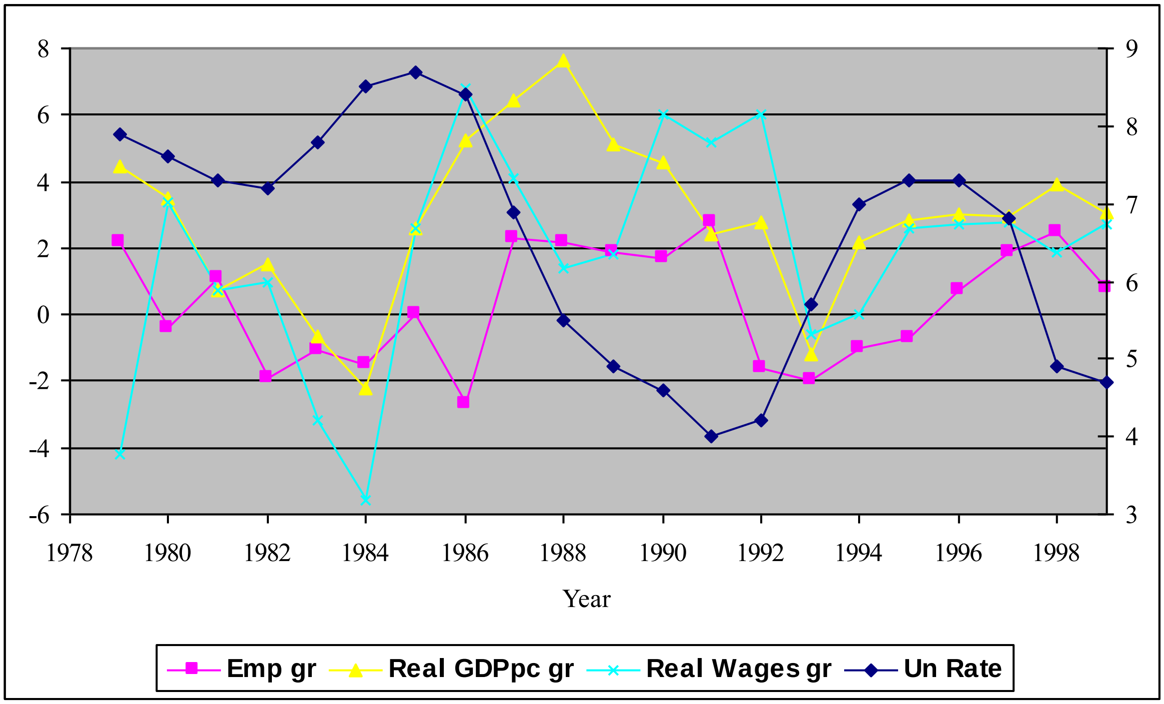
[43] Numbers refer to firm and multifirm classical strikes, reported in DEMQE, *Greves, Anual*. Number of strikes for years before 1987 were obtained from Mateus (1995), *Conflitos Colectivos de Trabalho, Anual 1995*.

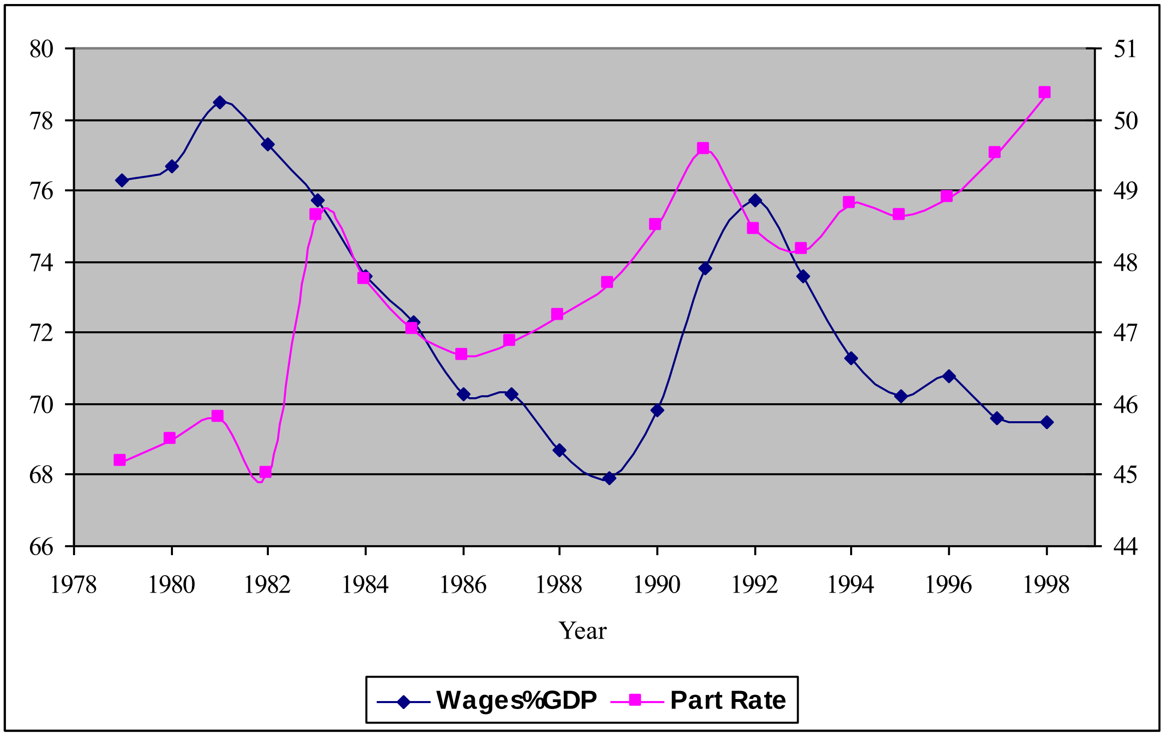
[44] Historically, Portugal entered the EEC on January 1st, 1986. Re-privatisations start around 1988 and the Escudo (the Portuguese currency) adheres the EMS (European Monetary System) in 1992.

[45] These, as the wage bill share were constructed from the long series of Économie Européenne (1998). The activity rate used below refers to the Continent and was constructed from INE´s *Inquérito ao Emprego*.



Graph 5

In Graph 6, we depicted the evolution of the wage bill share out of total GDP and the participation (activity) rate. The wage bill share consistently declined during the eighties, rose from 89 to 92 and fell subsequently, stabilizing in the last two years. The participation rate showed an upward trend behavior, moving in the opposite direction of real GDP growth rate and, roughly, of real wages growth rate.



Graph 6

2. To clarify the co-movement direction of strikes and economic aggregates, we calculated simple correlation coefficients between several macroeconomic variables for which we were able to collect consistent time series data. We present in Table 2 the correlations between strike indicators themselves. Table 3 exhibits the correlation coefficients between labor market aggregates and Table 4 correlations between labor market and nominal indicators. Finally, Tables 5.1 and 5.2 contain correlations between strike and the other variables; in these, we included both the growth rate as the level version of most inspected series.

The correlation between the total number of strikes and their severity, measured by either number of workers on strike, days lost or relative measures with respect to employment (a thousand employed) is positive but very low. All these other indicators are strongly and positively correlated, suggesting interchangeable interpretation of behavior – with the exception of days lost per striker, which roughly measures the (weighted) average length of strikes.

Table 2										
1987-1998	N. Strikes	N. Strikers	Days Lost	N. Strikers / Emp	N. Strikers EmpCN	Days Lost / Emp	Days Lost / EmpCN	. Strikers N. Strike	Days Lost / N Strikes	Days Lost / N Strikers
N. Strikes	1									
N. Strikers	0.233	1								
Days Lost	0.252	0.969 *	1							
N. Strikers / Emp	0.183	0.997 *	0.967 *	1						
N. Strikers / EmpCN	0.216	0.999 *	0.968 *	0.999 *	1					
Days Lost / Emp	0.192	0.966 *	0.996 *	0.972 *	0.969 *					
Days Lost / EmpCN	0.232	0.971 *	0.999 *	0.971 *	0.971	0.998 *	1			
N. Strikers / N. Strikes	-0.148	0.907 *	0.873 *	0.931 *	0.915 *	0.901 *	0.884 *	1		
Days Lost / N. Strikes	-0.172	0.862 *	0.892 *	0.888 *	0.870 *	0.920 *	0.901 *	0.0105	1	
Days Lost / N. Strikers	-0.101	-0.246	-0.0176	-0.252	-0.251	-0.0355	-0.0313	-0.239	0.0105	1
N. Strikes / Firm	0.647 *	0.611 *	0.665 *	0.589 *	0.601 *	0.636 *	0.653 *	0.353	0.388	0.138
Mean (s.d.)	268.417 (57.548)	107622.1 (69920.7)	133010.6 (84302.8)	54.750 (36.244)	23.974 (15.715)	67.833 (43.921)	29.596 (18.963)	408.417 (257.226)	506.083 (311.643)	10.299 (2.810)

Note: Strikes per firm are only available till 1997 – mean, 1.802; s.d., 0.425. (Firms are an underestimate).

Table 3 summarizes the correlation between labor market aggregates. On the upper diagonal block we register correlations for the whole 1979-1998 period; below the main diagonal, values use the sub-sample 1987-1998. Consistently, real wages growth rates are negatively correlated with the unemployment rate; real wages growth and per capita GDP growth seem positively correlated. The proportion of wages out of total GPD [46] is negatively correlated with growth rate of per capita GDP, growth rate of industrial production, of employment, and participation rate; the participation rate exhibits the same sign (negative) relation with the first two, but also with the unemployment rate [47]. In general, the industrial production growth rate has low correlations with all other indicators;

[46] By its nature, this variable shows a similar pattern as the Real wage costs index - in this as in tables below.
[47] Eventually, the latter supporting a "discouraged worker" effect.

interestingly, also the correlation between the unemployment rate and growth of real GDP per capita is low, even if, as expected, negative; positive and insignificant is the relation between productivity growth (GDP per worker) and the unemployment rate.

Table 3

1979-1998 / 1987-1998	Emp gr	Un Rate	Real GDP pc gr	Ind Prod gr	Real Wages gr (GDP)	Real Wages gr (PrivC)	Real Wage Costs	Real Wage Costs gr	Real GDP p Worker gr	Wages% GDP	Par Rate
Emp gr	1	-0.422 **	0.534 *	0.174	0.382 **	0.114	-0.249	0.513 *	-0.238	-0.343	0.204
Un Rate	-0.221	1	-0.262	0.175	-0.576 *	-0.431 **	0.407 **	-0.627*	0.150	0.262	-0.491 *
Real GDP pc gr	0.670 *	-0.0422	1	0.444 *	0.505 *	0.543 *	-0.460*	-0.00466	0.672 *	-0.546 *	-0.108
Ind Prod gr	0.589 *	-0.00298	0.659 *	1	0.0742	0.0525	0.0452	-0.225	0.417 **	-0.139	-0.435 **
Real Wages gr (GDP)	0.252	-0.501**	0.321	0.233	1	0.767 *	-0.113	0.740 *	0.242	-0.0377	0.000525
Real Wages gr (PrivC)	0.296	-0.446	0.264	0.236	0.909 *	1	-0.422**	0.401**	0.434 **	-0.326	0.177
Real Wage Costs	-0.526**	-0.321	-0.627*	-0.774 *	0.297	0.288	1	-0.00482	-0.138	0.960 *	-0.673 *
Real Wage Cost gr	0.329	-0.581 *	-0.0735	0.0516	0.812 *	0.804 *	0.449	1	-0.473 *	0.0964	0.314
Real GDP p Worker gr	-0.175	0.234	0.612 *	0.245	0.119	-0.00383	-0.304	-0.482	1	-0.184	-0.455 *
Wages%GDP	-0.568**	-0.313	-0.631*	-0.807 *	0.280	0.278	0.990 *	0.409	-0.262	1	-0.536 *
Par Rate	0.0781	-0.143	-0.464	-0.199	-0.157	0.0564	0.108	0.265	-0.696 *	0.166	1

In Table 4 we can inspect the correlations between nominal indicators and labor market variables. We can see that the signs switch sometimes when we confront the figures for 1979-1998 with the correlations for the smaller sample, 1987-1998. In this later period, all the variables, except for nominal wage cost levels and some of the real interest rate indicators, move consistently in the opposite direction to the unemployment rate, and to the participation rate. Real wage and real GDP per capita growth are consonant with inflation – either with the production price index growth as with private consumption deflator and money growth rates.

Table 4

1979-1998 (1987-1998)	Emp gr	Un Rate	Real GDP pc gr	Ind Prod gr	Real Wages gr (GDP)	Real Wages gr (PrivC)	Real Wage Costs	Real Wage Costs gr	Real GDP p Worker gr	Wages% GDP	Par Rate
GDPIP gr	-0.327 (0.322)	0.529 * (-0.648 *)	-0.273 (0.426)	0.341 (0.317)	-0.279 (0.578*)	-0.341 (0.467)	0.671 * (0.0932)	-0.287 (0.415)	0.0537 (0.177)	0.555 * (0.0234)	-0.638 * (-0.499**)
PCIP gr	-0.212 (0.270)	0.481 * (-0.627 *)	-0.328 (0.423)	0.304 (0.289)	-0.271 (0.617*)	-0.517 * (0.413)	0.759 * (0.105)	-0.191 (0.415)	-0.0779 (0.233)	0.635 * (0.0391)	-0.649 * (-0.567**)
Nom Wages gr	-0.186 (0.324)	0.318 (-0.661*)	-0.0759 (0.421)	0.383** (0.314)	0.113 (0.844*)	-0.0405 (0.731*)	0.653 * (0.205)	-0.00362 (0.652*)	0.159 (0.166)	0.562 * (0.151)	-0.668 * (-0.396)
Nom Wage Costs	0.126 (-0.390)	-0.509 * (0.249)	0.0512 (-0.692 *)	-0.459 * (-0.446)	0.133 (-0.419)	0.343 (-0.222)	-0.728 * (0.196)	0.247 (-0.0952)	-0.186 (-0.481)	-0.572 * (0.274)	0.850 * (0.822*)
Nom Wage Costs gr	-0.104 (0.385)	0.269 (-0.733*)	-0.286 (0.233)	0.250 (0.233)	0.0350 (0.806*)	-0.185 (0.730*)	0.696 * (0.301)	0.147 (0.805*)	-0.160 (-0.149)	0.619 * (0.233)	-0.526 * (-0.178)
M2M3 gr	-0.127 (0.437)	0.555 * (-0.304)	0.0235 (0.608*)	0.310 (0.0687)	-0.0581 (0.592*)	-0.187 (0.457)	0.691 * (0.158)	-0.221 (0.352)	0.254 (0.317)	0.552 * (0.111)	-0.799 * (-0.505**)
Int Rate sr	-0.319 (-0.0581)	0.256 (-0.570**)	-0.334 (0.0878)	0.0804 (0.0177)	-0.0745 (0.627*)	-0.242 (0.444)	0.537 * (0.448)	-0.0126 (0.484)	-0.0733 (0.133)	0.500 * (0.381)	-0.469 * (-0.508**)
Real Int Rate sr (GDP)	0.180 (-0.690 *)	-0.642 * (-0.0498)	0.0728 (-0.555**)	-0.535 * (-0.512*)	0.411 ** (0.299)	0.320 (0.104)	-0.563 * (0.767*)	0.499 * (0.277)	-0.184 (-0.0173)	-0.391 ** (0.747*)	0.591 * (-0.212)
Real Int Rate sr (PriC)	0.0267 (-0.764*)	-0.555 * (0.0591)	0.199 (-0.745*)	-0.453 * (-0.611*)	0.371 (0.105)	0.614 * (0.120)	-0.746 * (0.835*)	0.309 (0.209)	0.0443 (-0.192)	-0.568 * (0.821*)	0.643 * (0.0378)
Int Rate lr 1985-1998	-0.0868 (0.211)	0.206 (-0.466)	0.258 (0.420)	0.150 (0.252)	0.293 (0.715*)	0.428 ** (0.528**)	0.415 ** (0.186)	0.0272 (0.464)	0.335 (0.297)	0.173 (0.122)	-0.699 * (-0.597*)
Real Int Rate lr (GDP)	0.207 (-0.131)	-0.109 (0.154)	-0.0178 (0.174)	-0.252 (-0.00957)	0.514 * (0.584*)	-0.0544 (0.350)	0.260 (0.257)	0.482 * (0.297)	-0.150 (0.374)	0.261 (0.241)	-0.0778 (-0.465)
Real Int Rate lr (PriC)	-0.193 (-0.123)	0.503** (0.346)	0.0473 (0.103)	-0.0699 (-0.0308)	0.272 (0.461)	0.378 (0.456)	0.423 ** (0.265)	0.0593 (0.249)	0.249 (0.275)	0.293 (0.256)	-0.392 ** (-0.254)
Ef Nom Exch Rat	-0.0864 (0.188)	0.457 * (-0.261)	-0.177 (0.543**)	0.347 (0.122)	-0.0842 (0.573**)	-0.395 ** (0.408)	0.921 * (0.172)	-0.127 (0.225)	0.0719 (0.493)	0.799 * (0.111)	-0.801 * (-0.804*)
Ef Nom Exch Rat gr	0.258 (-0.157)	-0.619 * (-0.273)	0.373 (-0.196)	-0.228 (-0.111)	0.712 * (0.497)	0.736 * (0.566**)	-0.480 * (0.301)	0.551 * (0.489)	0.134 (-0.106)	-0.352 (0.385)	0.420 ** (0.521**)

Note: Long-run interest rates are only available from 1985 on.

The behavior of the number of strikes exhibits a different pattern in the two sub-periods, before and after middle eighties (which is consistent with the sign switches we remarked in Table 4). The signs of the correlations – see the two first lines of Table 5.1 – switch or the coefficients change significance for some indicators. Also, even for the later sub-sample, severeness moves sometimes in opposition to total number of strikes.

Restricting to the second period, strikes seem procyclical, specially its severity; number of strikers, lost days are negatively correlated with the unemployment rate, positively (even if less significantly) with real GDP per capita growth rate. All strike indicators are negatively, mostly, significantly, related to the participation rate, the population growth rate, and with the real wage level and also with the real expected wage level (constructed by the multiplication of the employment rate times the real wage index). All other correlations are weaker.

Consistently, the correlations with level indicators – real wages, expected wages, real GDP per capita, real GDP per worker – are usually negative and more significant than the correlations with growth rates, these being positive – and, in general, non-significant. It is not the purpose to discuss or model the appropriate cycle indicator – the business cycle is, in theory, a (more or less smooth) fluctuation around the long-run trend; but differencing (log-differencing) gives a completely different pattern for the conclusions. If levels are (closer to) the correct measure (and strikes should not themselves be differenced or log-differenced, i.e., consider growth rates of some of the strike indicators), strikes are countercyclical [48].

[48] In any event, theoretical implications of bargaining models would seem, in general, to apply to wage levels, not to its variability, wage changes; these could more appropriately be related to uncertainty, inducing strikes in most models – and being, in fact, positively correlated to strike indicators.

Table 5.1									
1987-1998	Pop	Pop gr	Emp	Emp gr	Un Rate	Real GDP pc	Real GDP pc gr	Ind Prod	Ind Prod gr
N. Strikes 1979-1998	0.255	0.415 **	-0.210	-0.398 **	0.470 *	-0.636 *	-0.564 *	-0.652 *	0.00872
N. Strikes 1986-1998	-0.302	-0.525 **	-0.0310	-0.611 *	0.0478	-0.0689	-0.182	-0.0397	-0.0723
N. Strikers	0.146	-0.482	-0.0868	0.158	-0.493	-0.546 **	0.356	-0.432	0.318
Days Lost	0.250	-0.516 **	-0.0472	0.229	-0.533 **	-0.495	0.456	-0.400	0.339
N. Strikers / Emp	0.183	-0.481	-0.147	0.176	-0.461	-0.593*	0.401	-0.492	0.323
N. Strikers / EmpCN	0.160	-0.474	-0.120	0.159	-0.468	-0.563**	0.373	-0.457	0.327
Days Lost / Emp	0.290	-0.511 **	-0.126	0.247	-0.487	-0.554**	0.506 **	-0.475	0.347
Days Lost / EmpCN	0.263	-0.509 **	-0.0858	0.229	-0.506 **	-0.519**	0.472	-0.431	0.347
N. Strikers / N. Strikes	0.338	-0.450	-0.253	0.316	0.417	-0.687 *	0.532 **	-0.605 *	0.371
Days Lost / N. Strikes	0.479	-0.460	-0.226	0.419	-0.439	-0.633 *	0.656*	-0.575**	0.417
Days Lost / N. Strikers	0.483	0.0872	0.327	0.414	-0.156	0.392	0.273	0.338	0.137
N. Strikes / Firm	-0.0644	-0.758 *	0.190	-0.0328	-0.633 *	-0.399	0.237	-0.212	0.0871

Note: Strikes per firm are only available till 1997.

The number of strikes is positively correlated to the proportion of wages out of GDP, yet its severeness is negatively related to it.

Table 5.1 (Cont.)

1987-1998	Real Wages (GDP)	Real Wages (GDP) x (1-ur)	Real Wages gr (GDP)	Real Wages x(1-u) gr (GDP)	Real Wages (PrivC)	Real Wages (PrivC) x (1-ur)	Real Wages gr (PrivC)	Real Wages x(1-u) gr (PrivC)	Real Wage Costs	Real Wage Costs gr	Real GDP p Worker	Real GDP p Worker gr	Wages% GDP	Par Rate
N. Strikes 1979-1998	-0.502 *	-0.522 *	-0.242	-0.301	-0.568 *	-0.581 *	-0.345	-0.382 **	0.730*	-0.0672	-0.650 *	-0.221	0.710 *	-0.462 *
N. Strikes 1986-1998	0.0399	0.0375	0.228	0.0364	-0.00263	-0.00454	0.512 **	0.272	0.388	-0.0416	-0.0827	0.346	0.413	-0.0804
N. Strikers	-0.641*	-0.581 *	0.259	0.243	-0.672*	-0.622 *	0.0459	0.0673	-0.196	0.0563	-0.598*	0.290	-0.221	-0.477
Days Lost	-0.616 *	-0.548 **	0.264	0.308	-0.622*	-0.564 **	0.100	0.175	-0.248	0.0269	-0.552**	0.345	-0.258	-0.438
N. Strikers/ Emp	-0.684*	-0.630 *	0.249	0.246	-0.713*	-0.667 *	0.0258	0.0631	-0.219	0.0238	-0.635*	0.331	-0.246	-0.529 **
N. Strikers/ EmpCN	-0.657*	-0.601 *	0.246	0.234	-0.687*	-0.640 *	0.0297	0.0563	-0.214	0.0318	-0.609 *	0.312	-0.240	-0.502**
Days Lost / Emp	-0.670*	-0.610 *	0.249	0.306	-0.674*	-0.622 *	0.0734	0.164	-0.275	-0.0136	-0.599**	0.394	-0.289	-0.503 **
Days Lost / EmpCN	-0.637*	-0.574 **	0.254	0.299	-0.643*	-0.589 *	0.0852	0.163	-0.263	0.00472	-0.569**	0.368	-0.275	-0.468
N. Strikers / N. Strikes	-0.800*	-0.755 *	0.158	0.224	-0.808*	-0.770 *	-0.0810	0.0353	-0.330	-0.0681	-0.713*	0.357	-0.368	-0.599*
Days Lost / N. Strikes	-0.783*	-0.732 *	0.142	0.284	-0.760*	-0.717 *	-0.0446	0.141	-0.419	-0.114	-0.662*	0.412	-0.443	-0.554**
Days Lost / N. Strikers	0.230	0.263	-0.156	0.122	0.354	0.387	0.0951	0.343	-0.292	-0.0929	0.352	-0.0820	-0.246	0.415
N. Strikes / Firm	-0.360	-0.268	0.650*	0.575 **	-0.410	-0.330	0.554**	0.493	0.277	0.377	-0.505**	0.319	0.281	-0.291

The pattern in Table 5.2 shows, to the exception of the Nominal wage costs index, an always positive and usually significant relation between strike indicators (with the exception of strike duration) and the nominal variables growth rates, including nominal interest rates; the relation to levels has the opposite sign.

In theoretical models, the higher the discount factor, hence, the lower the interest rate (in most cases, the real rate would be appropriate), the higher strike involvement would be expected. The relation to the real interest rates is usually non-significant, the larger correlations in absolute value being, in fact, negative; strike duration - Days Lost/ N. Strikers - is significantly (and negatively related) to all real interest rate indicators, and with one of the long-run real interest rates.

Table 5.2												
1987-1998	GDPIP	GDPIP gr	IPCIP	PCIP gr	Nom Wages	Nom Wages x(1-ur)	Nom Wages gr	Nom Wages) x(1-u) gr	Nom Wage Costs	Nom Wage Costs gr	IM2M3	M2M3 gr
N. Strikes 1979-1998	-0.631 *	0.686 *	-0.626 *	0.690 *	-0.599 *	-0.601 *	0.611 *	0.558 *	-0.610 *	0.684 *	-0.615 *	0.534 *
N. Strikes 1986-1998	-0.0313	0.344	-0.0160	0.217	-0.0209	-0.0195	0.373	0.280	0.00940	0.263	-0.0729	0.168
N. Strikers	-0.646 *	0.736 *	-0.636 *	0.780 *	-0.661 *	-0.652 *	0.601 *	0.574 **	-0.651 *	0.513 **	-0.656 *	0.292
Days Lost	-0.614 *	0.702 *	-0.616 *	0.724 *	-0.623 *	-0.611 *	0.581 *	0.586 *	-0.627 *	0.474	-0.603 *	0.302
N. Strikers / Emp	-0.686 *	0.741 *	-0.677 *	0.789 *	-0.700 *	-0.692 *	0.599 *	0.578 *	-0.693 *	0.498**	-0.691 *	0.333
N. Strikers / EmpCN	-0.658 *	0.731 *	-0.649 *	0.777 *	-0.674 *	-0.665 *	0.592 *	0.567 **	-0.666 *	0.497 **	-0.667 *	0.297
Days Lost / Emp	-0.663 *	0.709 *	-0.665 *	0.735 *	-0.671 *	-0.661 *	0.578 *	0.589 *	-0.679 *	0.456	-0.647 *	0.351
Days Lost / EmpCN	-0.633 *	0.703 *	-0.634 *	0.726 *	-0.642 *	-0.630 *	0.576 *	0.582 *	-0.647 *	0.462	-0.620 *	0.312
N. Strikers / N. Strikes	-0.774 *	0.749 *	-0.773 *	0.797 *	-0.788 *	-0.783 *	0.560 **	0.570 **	-0.794 *	0.453	-0.761 *	0.443
Days Lost / N. Strikes	-0.741 *	0.701 *	-0.753 *	0.726 *	-0.749 *	-0.741 *	0.521 **	0.571 **	-0.773 *	0.396	-0.701 *	0.457
Days Lost / N. Strikers	0.302	-0.247	0.251	-0.364	0.318	0.333	-0.234	-0.0906	0.257	-0.215	0.391	-0.119
N. Strikes / Firm	-0.482	0.636 *	-0.467	0.658 *	-0.475	-0.455	0.730 *	0.679 *	-0.431	0.605 *	-0.520**	0.402

Note: Strikes per firm are only available till 1997.

Table 5.2 (Cont.)								
1987-1998	Int Rate sr	Real Int Rate sr (GDP)	Real Int Rate sr (PriC)	Int Rate lr	Real Int Rate lr (GDP)	Real Int Rate lr (PriC)	Ef Nom Exch Rat	Ef Nom Exch Rat gr
N. Strikes 1979-1998	0.581 *	-0.540 *	-0.593 *	0.591 *	0.0218	0.502 **	0.611 *	-0.450 *
N. Strikes 1986-1998	0.317	-0.0748	0.237	0.285	-0.118	0.291	0.267	0.419
N. Strikers	0.610 *	0.00126	-0.283	0.657 *	0.143	-0.167	0.447	-0.103
Days Lost	0.509 **	-0.155	-0.403	0.588 *	0.0405	-0.225	0.463	-0.0713
N. Strikers / Emp	0.607 *	-0.0121	-0.310	0.669 *	0.164	-0.153	0.488	-0.148
N. Strikers / EmpCN	0.603 *	-0.00534	-0.294	0.656 *	0.150	-0.161	0.457	-0.126
Days Lost / Emp	0.509 **	-0.165	-0.428	0.606 *	0.0727	-0.199	0.511 **	-0.128
Days Lost / EmpCN	0.508 **	-0.156	-0.410	0.593 *	0.0536	-0.214	0.479	-0.0976
N. Strikers / N. Strikes	0.556 **	-0.131	-0.450	0.652 *	0.106	-0.231	0.534 **	-0.338
Days Lost / N. Strikes	0.426	-0.322	-606 *	0.566 **	-0.00998	-0.300	0.539 **	-0.330
Days Lost / N. Strikers	-0.559 **	-0.757 *	-0.544 **	-0.457	-0.626 *	-0.400	-0.194	0.0538
N. Strikes / Firm	0.714 *	0.251	0.0730	0.699 *	0.325	0.151	0.583 *	0.310

Note: Long-run interest rates are only available from 1985 on.

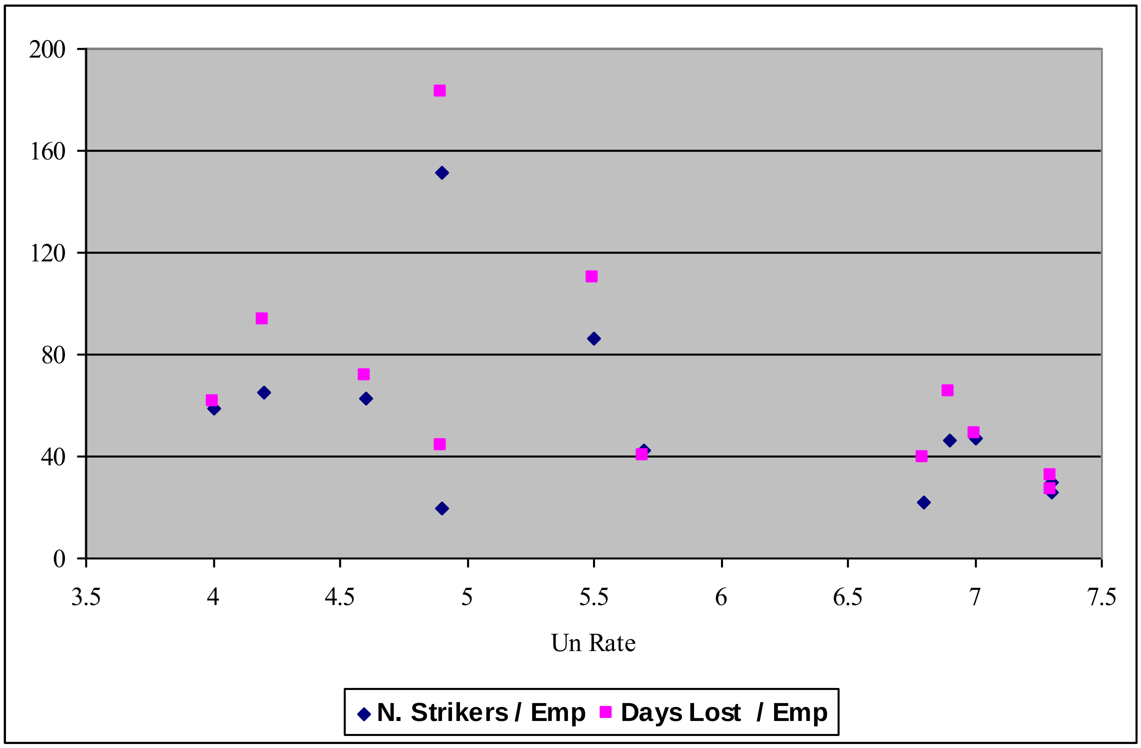
A remark can be made at the forefront with respect to the switch in the signs of the correlations of strike aggregates with levels and growth indicators in the presence of inflation: due to sluggishness of upward adjustment of real wages under fixed-period contract agreements, unanticipated inflation may more easily trigger worker discontent – hence, periods of higher nominal changes present more strike occurrences [49]; the inspection of the impact of inflation on strike activity for the U.S. and findings consistent with (and) that explanation can be traced to Mauro (1982) [50] and Vroman (1989); Reilly (1996) also finds a positive effect of the inflation rate on strike incidence for Ireland. Higher levels of

[49] Cramton and Tracy (1994) after controlling for other variables, find a negative effect of inflation uncertainty but a positive effect of stock price uncertainty on strike activity; but they aim to measure dispersion – which is not the argument here invoked.

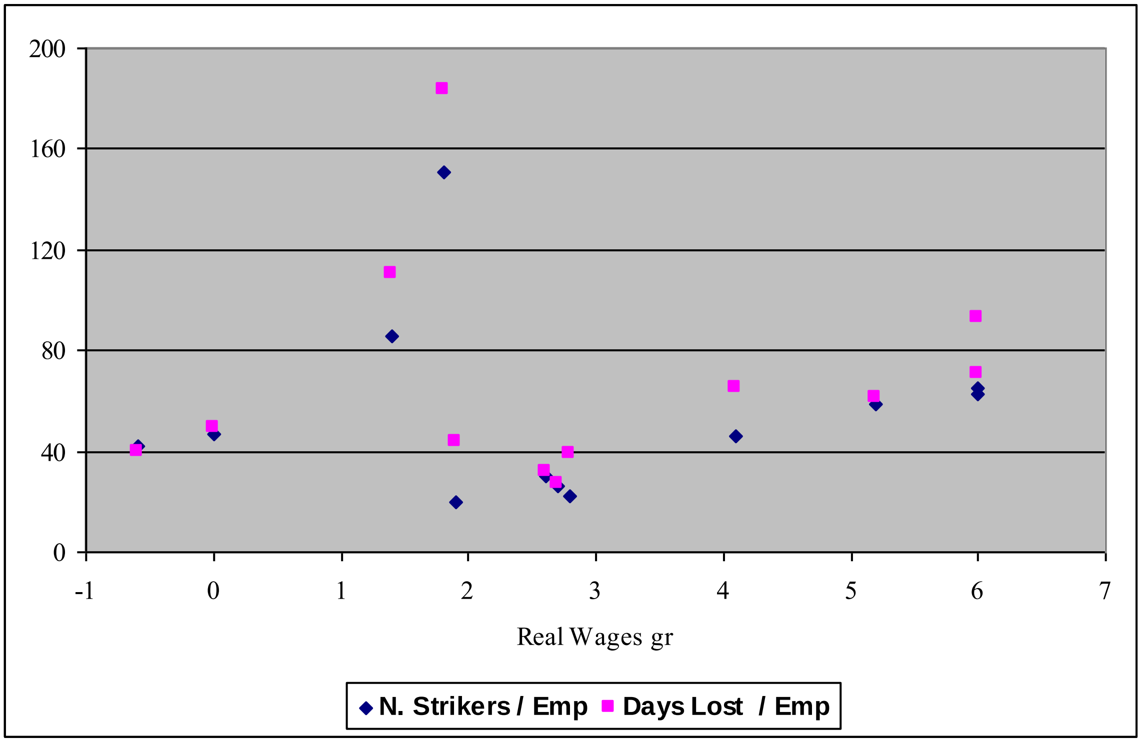
[50] Including a Cost of Living Adjustment clause indicator in strike regressions – he find a negative even if insignificant effect; in particular, he analyzes the impact of divergent expectations of workers and firm concerning inflation on strike incidence.

the variables (of positively valued aggregates, i.e., excluding unemployment or the interest rate), especially real but also nominal, as consistent with higher wellbeing of the economy, and diminish disruptions.

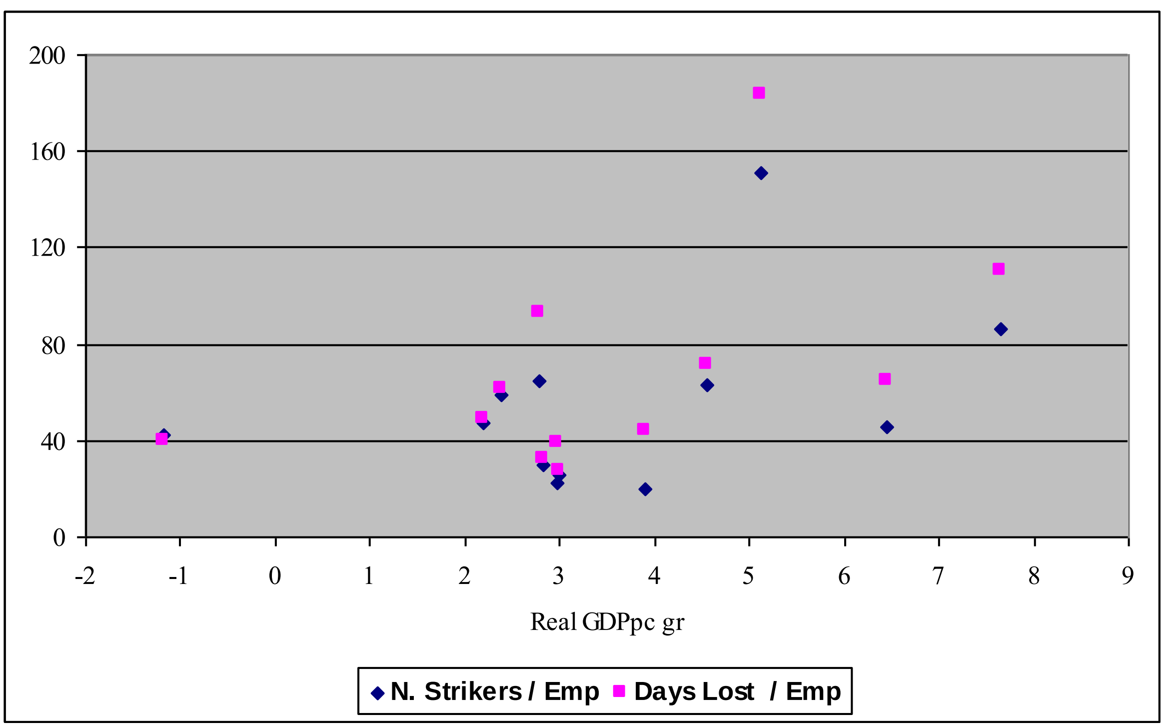
3. Some plots of strike incidence and severeness against some of the above indicators are presented below, showing (some) procyclicity.



Graph 7



Graph 8



Graph 9

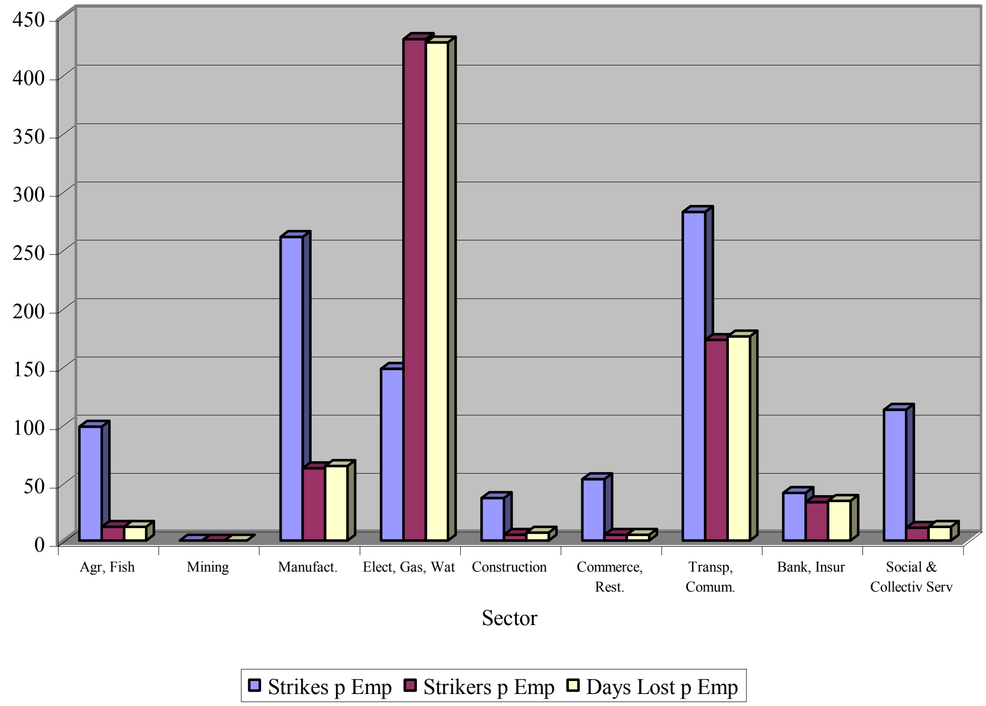
1.3. Industry Patterns of Strike Inflictions

1. We present below sector disparities in strike occurrences, evident in Portuguese data for years 1993 and 1994. Concurrently, we advance some characteristics of the data we use later in the regressions. In these, we mainly combined information from “Greves” and “Quadros de Pessoal” from Labour Ministry. Data does not include Public Administration (30 out of 326 classical strikes in 1994, 58 out of 286 in 1993), once sector information in “Quadros de Pessoal” does not include them, and more detailed information about constructed variables, corresponding cross correlations and means are contained in Appendices 1 and 2.

In graphs 10, 11 and 12 we report the one-digit sector information, most of it directly published in the official statistics. Given that we tried to use two-digit information, for which such figures were not available, we constructed the same indicators from the disaggregate data using two different sources of employment – the denominator of the two most relevant ratios –, “Quadros de Pessoal” and “Contas Nacionais”, and compare the structure – in graphs 13 to 17 – to the previous one.

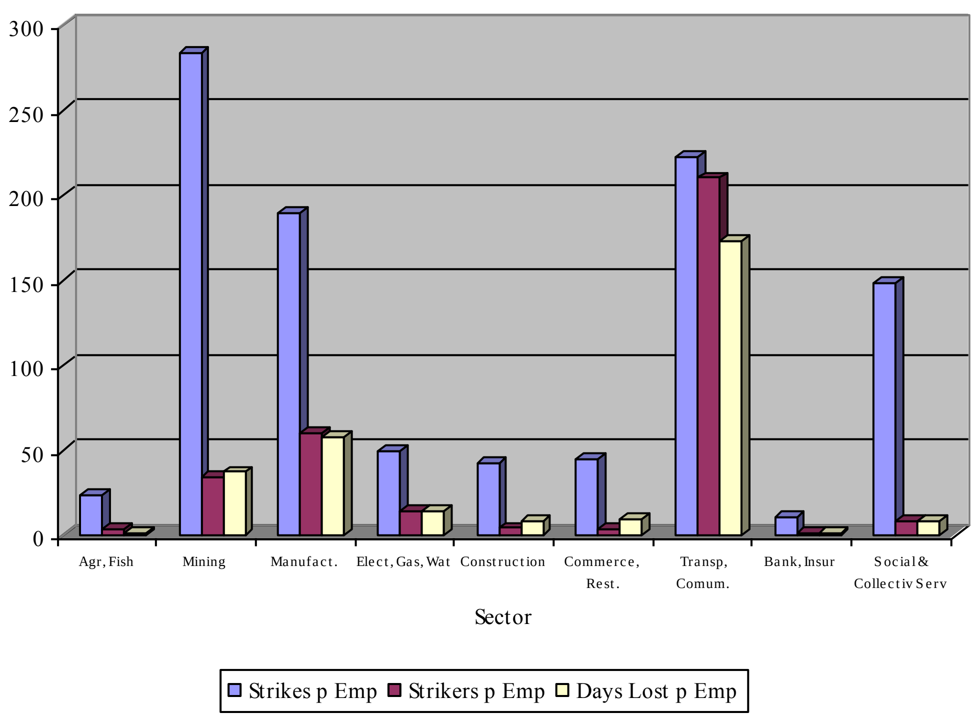
In both years, Transports and Communications and Manufacturing show a higher level of incidence of days and strikers per employment – traditionally sectors with higher capital intensity and larger firms; Agriculture, Commerce and Restauration and Construction have low level of disputes. Electricity, Gas and Water – which also has the largest firm size – has high disputes in 1994. Mining has low strike activity in 1994, Banking and Insurance in 1993.

Strikes per employment show a somewhat different pattern than the other indicators – possibly reflecting some interaction with firm size in the sector. Yet the two highest sectors according to the previous indicators remain high.



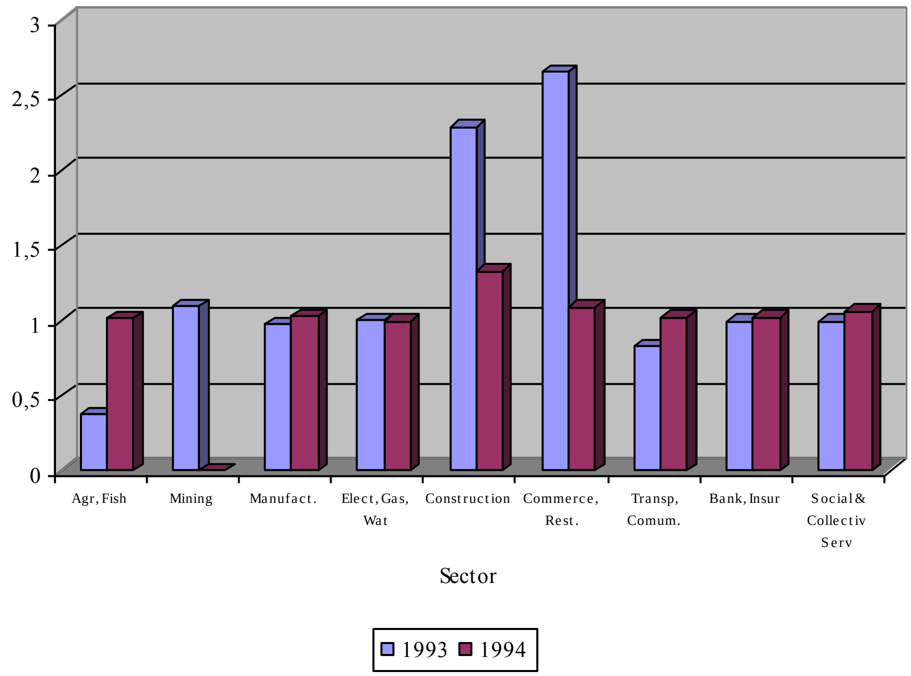
Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 10 – Portugal, 1994 from *Greves (1997)*



Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 11 – Portugal, 1993 from *Greves (1997)*

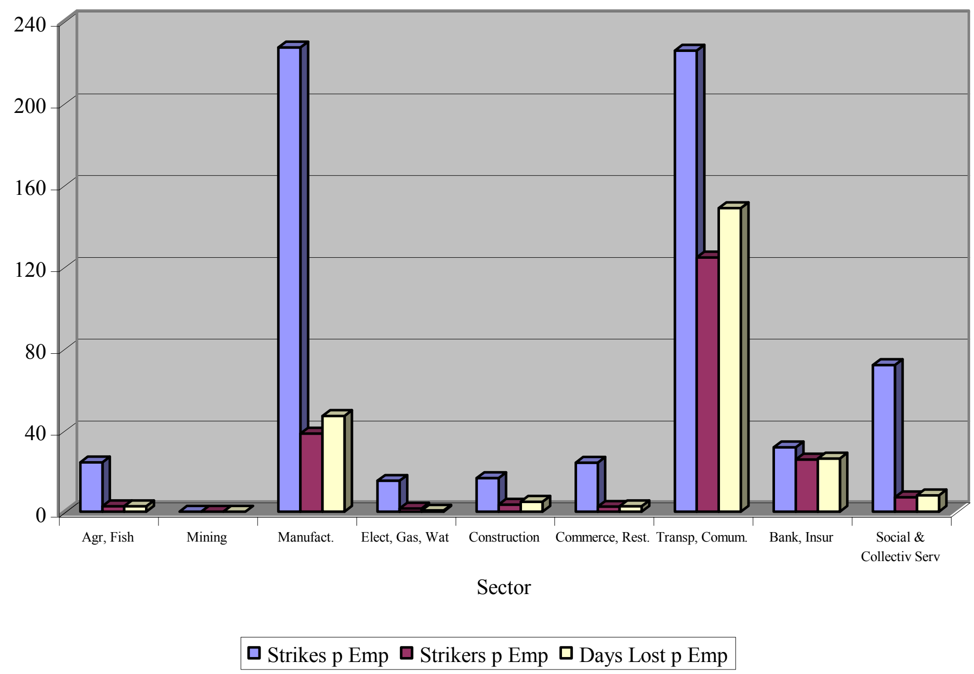


Graph 12 – Portugal, Days Lost per Striker from *Greves (1997)*

Strike length – in graph 12 – is quite stable for most of the sectors, usually lasting around one day on average. It is mildly longer in two sectors of low incidence – Commerce and Construction, specially in 1993.

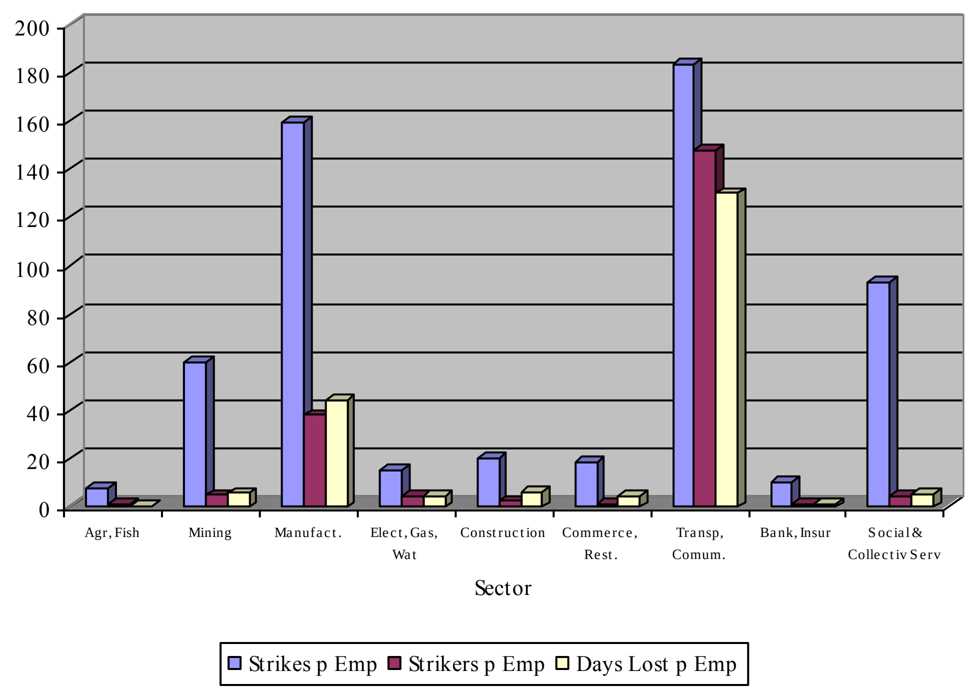
In our sample, the only sector for which some difference is encountered is Electricity, Gas and Water which shows low (scaled) strike activity in 1994 in our data even if not in other statistics. We confirmed the size effect dividing by different employment series and obtained the same pattern below, hence accepted our scaling.

Strike length – graph 17 – seems less homogeneous than in graph 12, even if the same trend is revealed for 1993; in 1994, Manufacturing and Transportation also show lengthier strikes in our data.



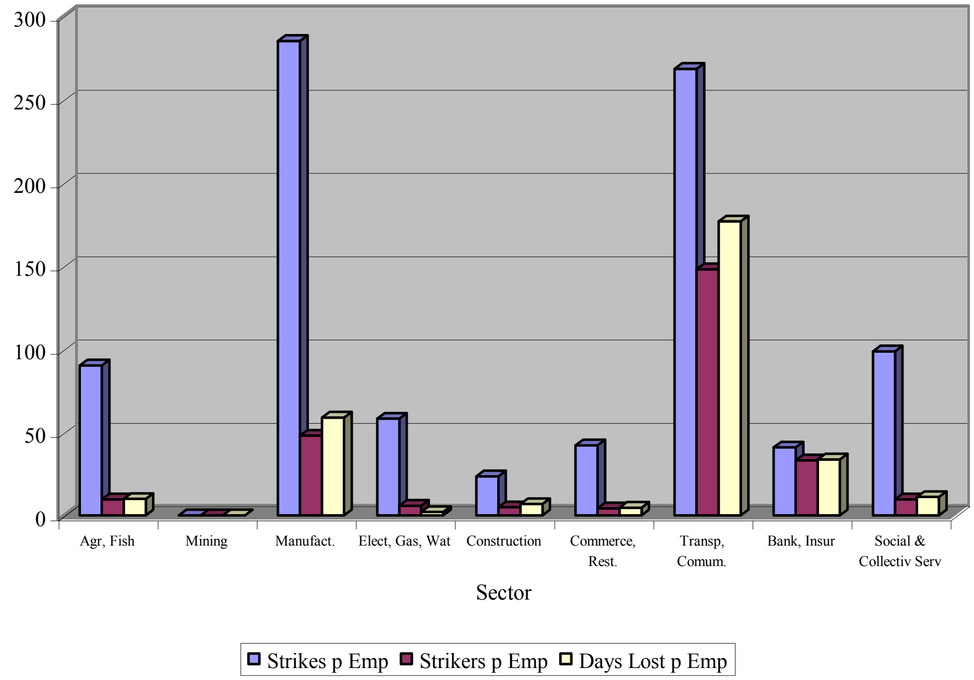
Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 13– Portugal, 1994, Paid Employment from *National Accounts*



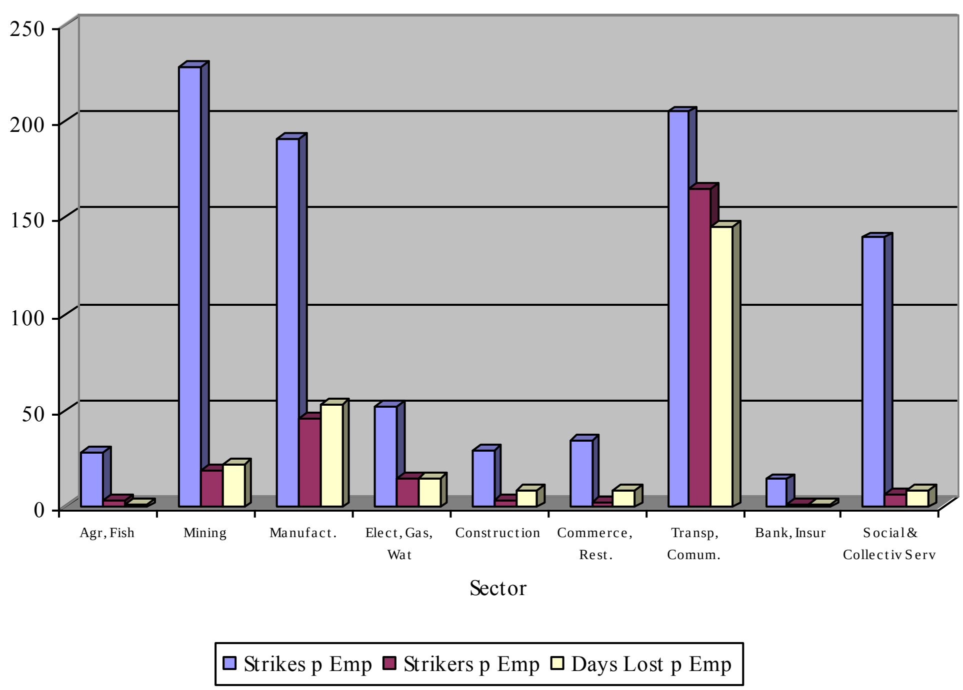
Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 14 – Portugal, 1993, Paid Employment 1994 from *National Accounts*



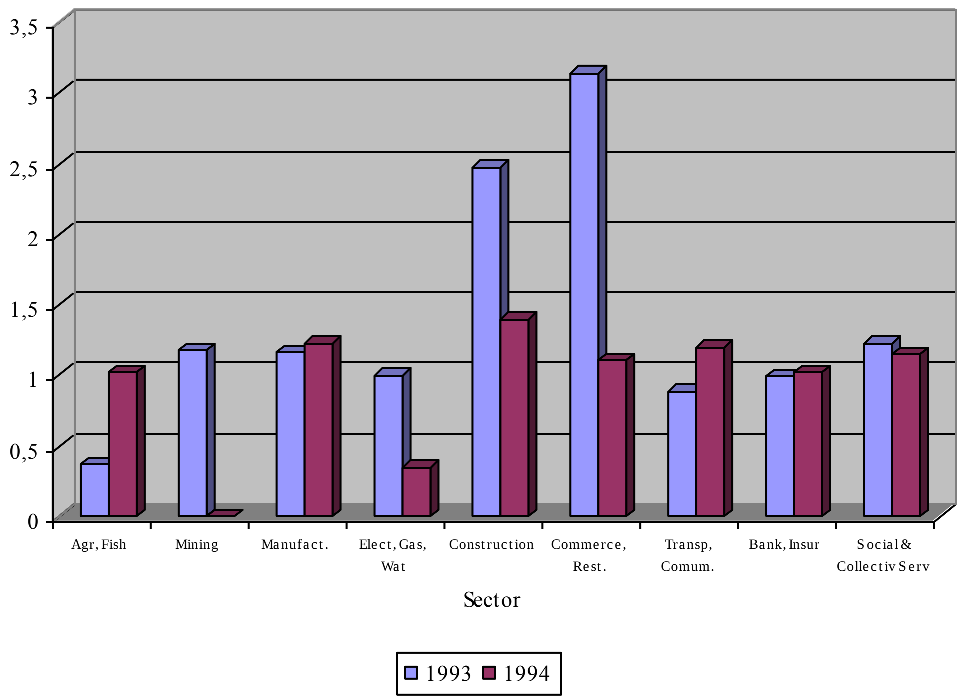
Strikes per million employed; Strikes and Days Lost per thousand employed

Graph 15 – Portugal, 1994, Employment from *Quadros de Pessoal*



Strikes per million employed; Strikes and Days Lost per thousand employed

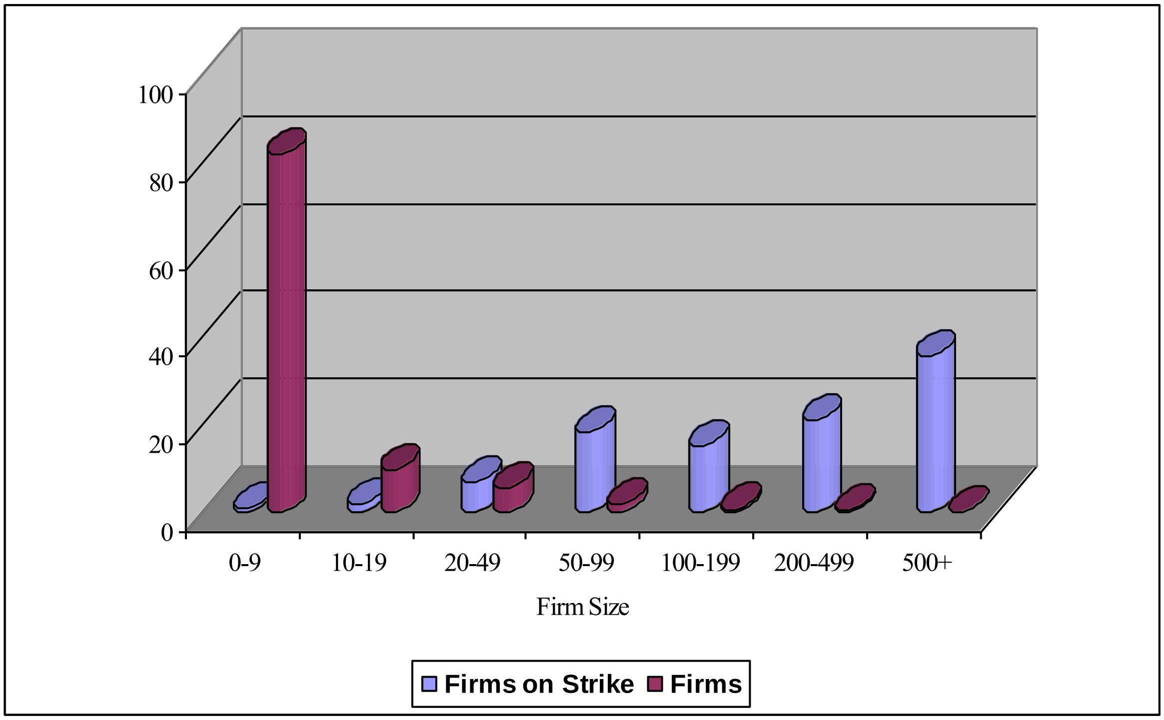
Graph 16 – Portugal, 1993, Employment from *Quadros de Pessoal*



Graph 17 – Portugal, from Disaggregated Data

2. Finally, we confront in Graph 18 the distribution of the number of firms by size [51] and firms affected by strikes in 1997 [52]. Clearly, strikes are more frequent at large firms, the switching occurring for the class of 20-49 employed people.

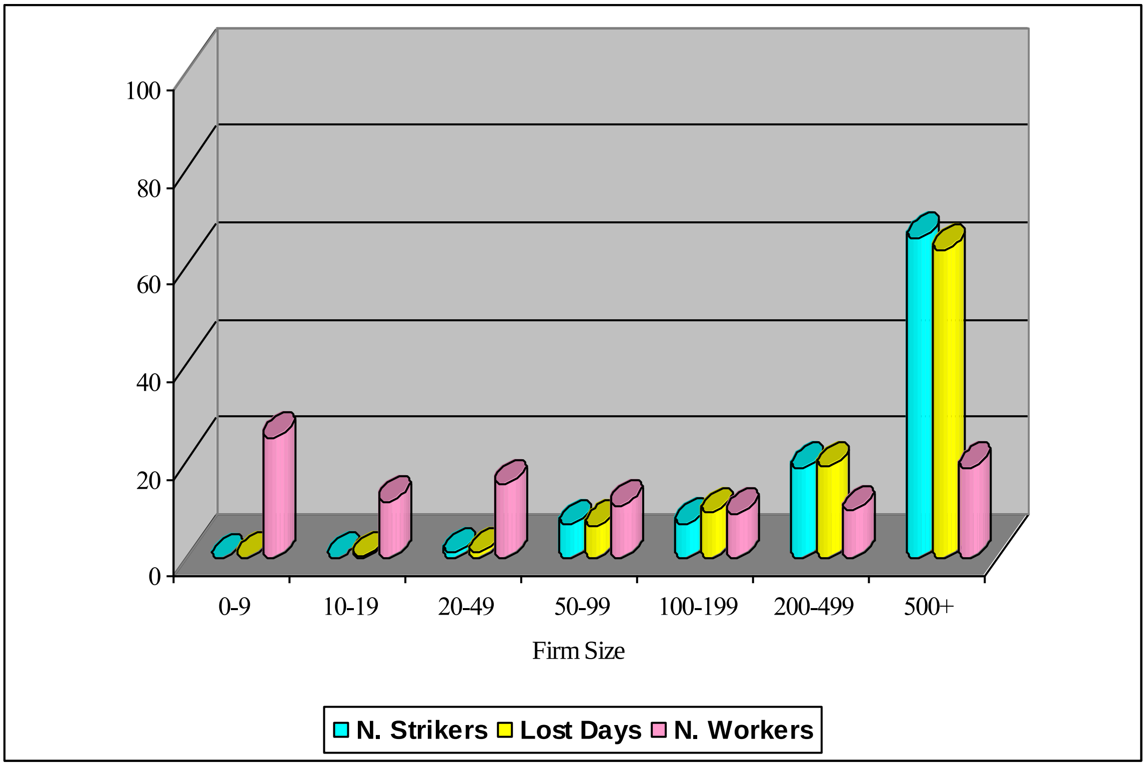
[51] From DEMQE, *Quadros de Pessoal, 1997*, Table 7.
[52] From DEMQE, *Greves, Anual/1997*, Table 7, Total Classic Strikes.



Graph 18

Repeating the same exercise with workers [53], number of strikers and days lost [54], that relation is also observed, with the switch at size class of 200-499 people employed.

[53] From DEMQE, *Quadros de Pessoal, 1997*, Table 9.
[54] From DEMQE, *Greves, Anual/1997*, Table 7, Total Classic Strikes.



Graph 19

Notice that other studies record higher wages being paid by larger firms, result being connected to difficult monitoring – i.e., efficiency wage arguments.

2. A Signaling Model of Strikes.

2.1. Context and Notation.

1. Most explanations of strike incidence or length associate it with union behavior. In modern theories, modelled within the context of asymmetric information; strikes are the means by which the firm signals its unprofitability and thus, its inability to pay for required wages, to the union; in others, they are screening devices used by the union to discriminate between profitable and unprofitable firms.

We want to advance a simple model of strikes where we highlight another feature of strike behavior: that its occurrence "burns" workers´ time, that individuals are different in preferences towards income and leisure and in productivity, and that firms may have difficulty in discriminating worker types in contract design.

We can see the following framework – formulated in 2.4 and 2.5 below - as a modification of Spence (1973) signalling model of education. By striking, workers are able to signal to the firm that they are of higher productivity; if some workers strike and others do not – the former are willing to bear the cost of striking while the others are not – in some cases, the firm is able to distinguish who is who.

More distantly, the model could complement Wilson´s (1988) research, a screening model, on the use of credentials by a monopsonist firm for purposes of wage discrimination of equally productive workers´ according to their reservation wages. Our framework assumes different worker productivities, as well as different consumer-worker preferences, recovers some of Spence´s conclusions in case of effective differentiation, and, if we think of a world where task-matching is important in enhancing productivities potential, may render the (a) credential beneficial.

2. Consider we have two individuals, call it 1 and 2 with hourly value of each marginal product W_1 and W_2 respectively with $W_1 > W_2$. The two workers, who know their marginal product, have preferences associated with general utility functions $U^i(O_i,Y_i)$, i=1,2, increasing and quasi-concave in the arguments, leisure consumption, O_i, and income Y_i. Let H_i denote hours of work of individual i, and T_i his time endowment, i.e., $H_i = T_i – O_i$. If workers´ hours are paid according to the marginal product, $Y_i = W_i H_i$.

Let us picture the equilibrium in (H_i,Y_i) space – see Fig. 1. Ideally, each worker would be paid according to his marginal productivity – we abstract from altruistic or distributive considerations - and choose on the corresponding budget constraint his most preferred bundle, i.e., the "basket" (H_i,Y_i) that maximizes his utility - $U^i(T_i – H_i,Y_i)$ [55] -, the point on the worker´s b.c. that allows him the highest (more to the northwest) indifference curve, the traditional tangency of worker´s indifference curve and wage line.

If the firm knows which worker is which, then the workers can and will locate on the "correct" spots.

---

[55] We could introduce exogenous non-labor earnings V_i in the utility function, that is, consider $U^i(T_i – H_i, Y_i+ V_i)$. One can show that if U(O,R) is quasi-concave in the two arguments, O and R, then, $U_O(O,R) / U_R(O,R) = - U_H(T-H,Y+V) / U_Y(T-H,Y+V)$, the slope of an indifference curve in space (H,Y), is expected to decrease with T – leading to higher hours being chosen - and increase with V – lowering optimal hours.

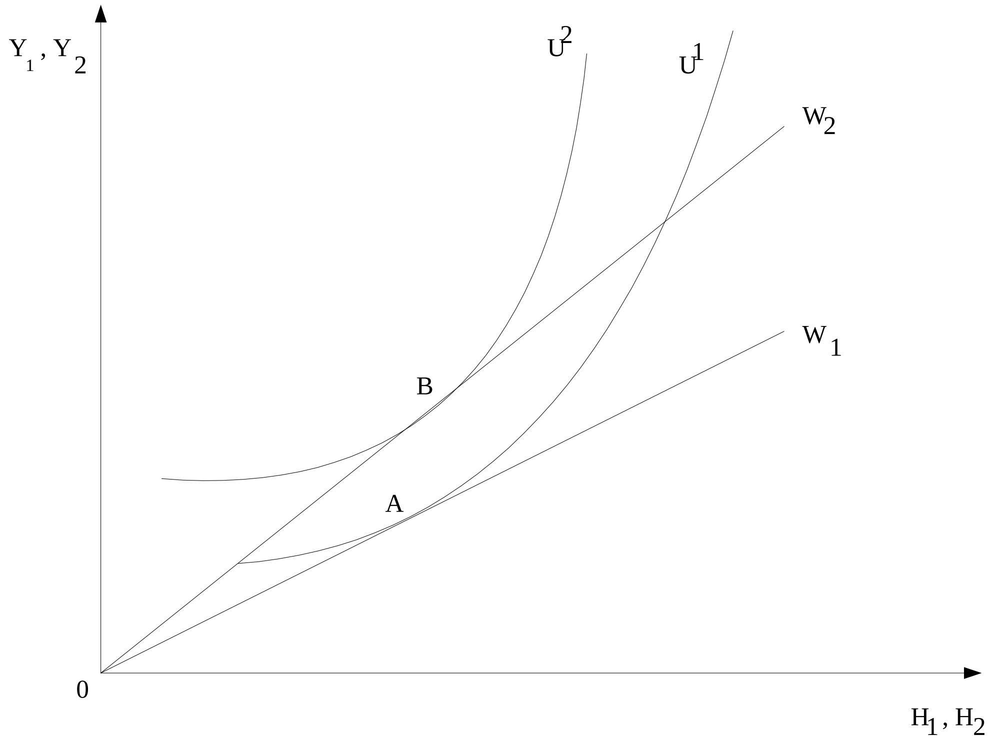


Fig. 1

2.2. Part-Time Contracts as Screening Devices.

Suppose that the firm cannot monitor workers´ productivity. Then, in the absence of other restrictions, a worker of type 1 will always claim he is of type 2 and attain his most preferred bundle on the higher budget constraint. If task assignment is not a problem, the firm can offer the average productivity to everyone – on average, it will collect the same product and pay the same wage. But if it is, and the fulfilling of the higher marginal product depends on knowing who is who, that possibility collapses and we arrive at the adverse selection problem dilemma.

If the firm can monitor and enforce hours and is allowed to offer "restricted budget contracts" - in the insurance market problem studied by Rothschild and Stiglitz (1976) that would amount to say the insurance company can fix both the premium and the coverage, or offer a premium conditional on coverage purchased, i.e., non-linear pricing -, that is, say, that fix both wage and hours of work, in certain conditions, the market may achieve a separating equilibrium. In a certain manner, adverse selection would be the cause for "tied sales" [56].

Case 1: Consider that 2´s most preferred bundle at wage W_2, B, is to the right of point C (or to the left of point D) in Fig. 2; if the firm offers (W_1,H_A) and (W_2,H_2*), where H_A and H_2* are the hours chosen by each type when they are paid their marginal product, workers will automatically self-select to their optimal bundles. Alternatively, we could think of a type of contract such that wage W_2 would only be attained with more than H_C hours of work (less than H_D, hours in point D, if B is to the left of D).

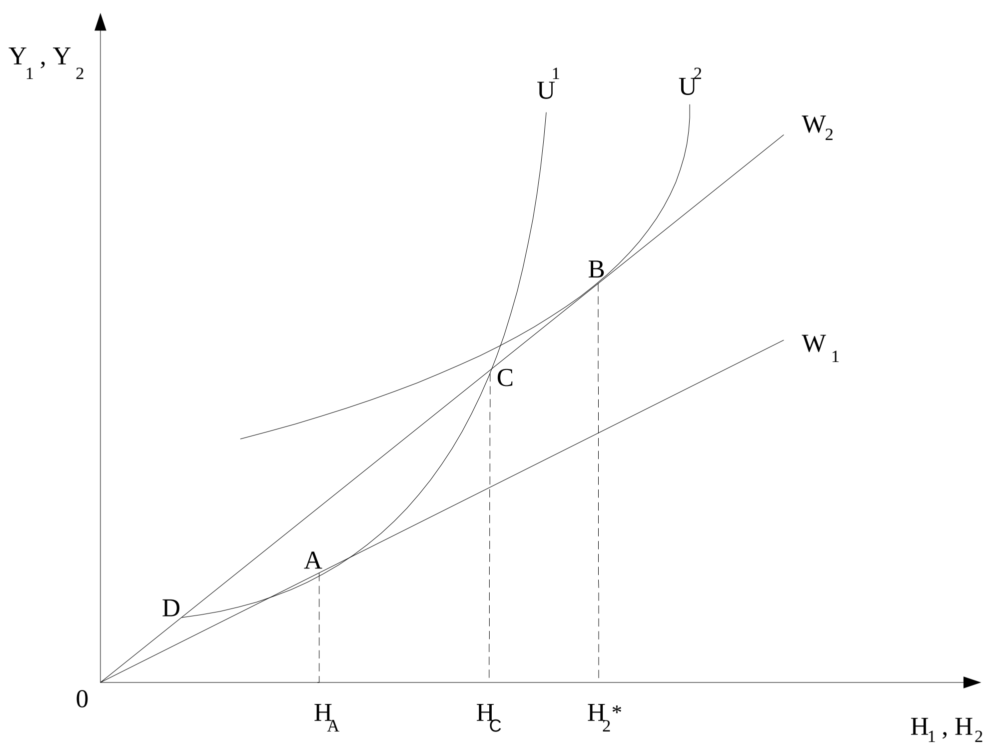


Fig. 2

Case 2. Suppose that 2´s most preferred bundle at wage W_2 lies between C and D and the utility he gets at C and/or at D is higher than the one he gets at A – see Fig. 3; if the firm offers two contracts (W_1,H_A) and (W_2,H_r) – r=C,D according to whether C or D is the best for 2 -, workers will again self-select correctly. If C yields, for 2, higher utility

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[56] See Rosen (1974) and Lewis (1969) there cited. Also Welch (1969). Their analysis would explain *ex post*, observed, bundling in the case of perfect information, that is, A and B of Fig. 1. Not "bundled contracts", as Rothschild and Stiglitz and the analysis below suggest.

than D, the contract could be written as: $W = W_1$ for $H \leq H_C$; $W = W_2$ for $H > H_C$. In the opposite case, $W = W_2$ for $H < H_D$; $W = W_1$ for $H \geq H_D$.

In this case, however, if the average productivity in the economy (properly weighted by the hours chosen by each type at that wage) is above $\bar{W}$, the wage associated with the b.c. that is tangent to 2´s indifference curve crossing C – i.e., if high productivity workers are in a sufficient proportion – there will be no separating equilibrium. A firm offering $\bar{W}$ at free work schedules will attract all workers.

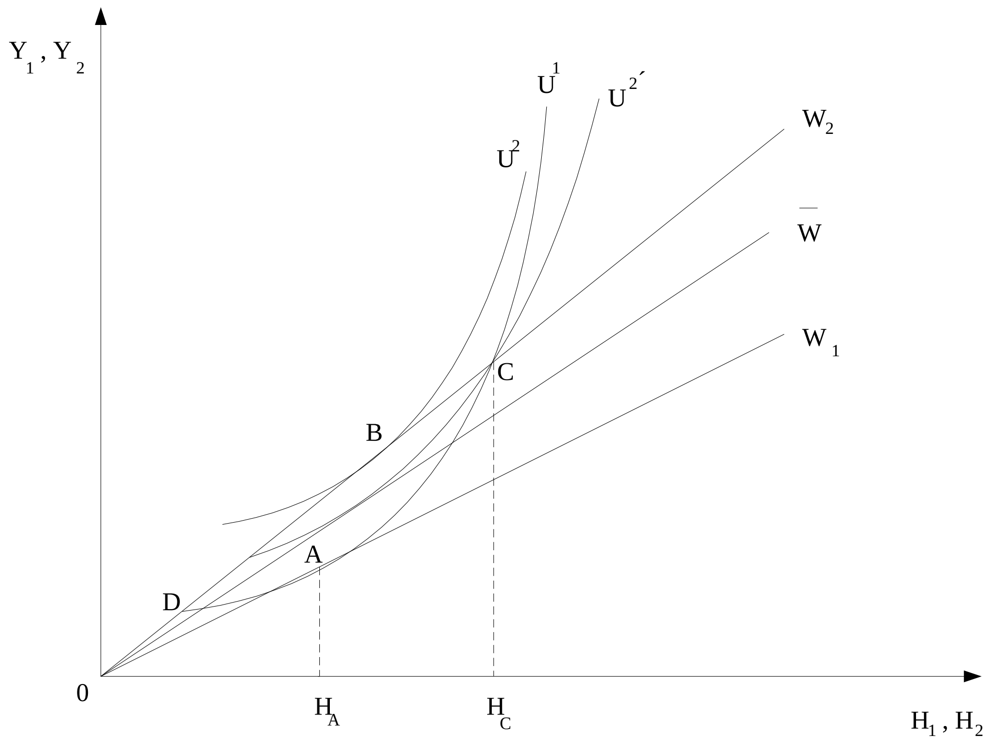

Fig. 3

Case 3. 2´s most preferred bundle at wage W_2 lies between C and D and the utility he gets at C or D is lower than the one he gets at A, in Fig. 4. Then, there is no separating equilibrium (as there won't be if workers have identical preferences).

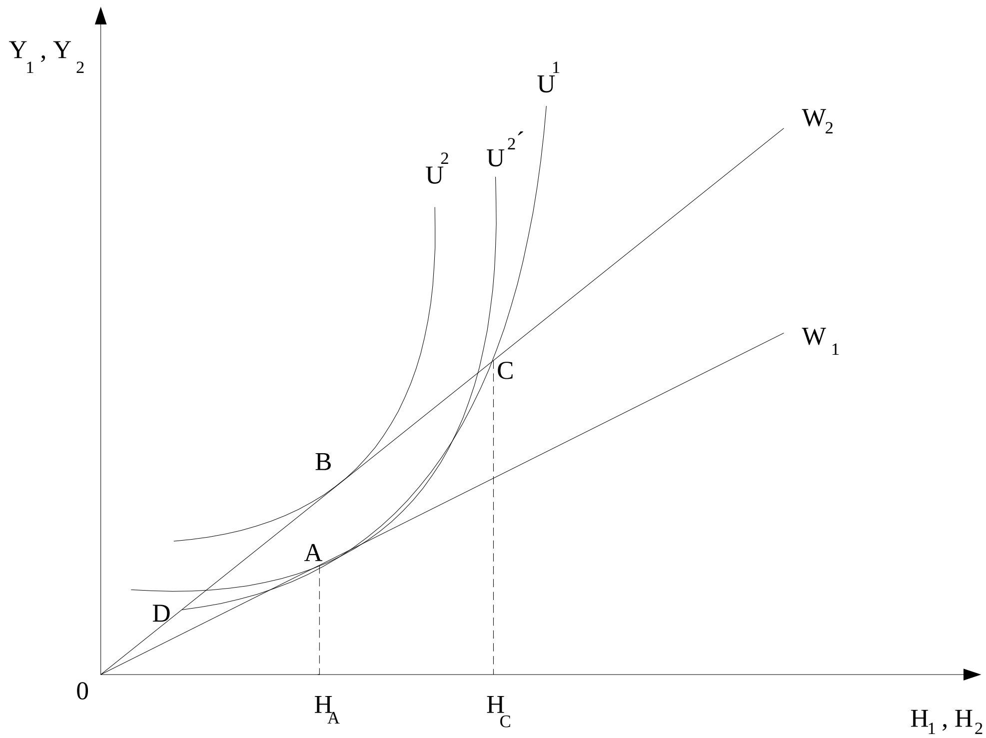

Fig. 4

The above distinction illustrates the well-known single-crossing property, not satisfied if one of the individual´s indifference curve is everywhere more convex than the other´s. Bundled hour-wage contracts are an effectively separating and revealing signal of the individuals´ productivity in some cases, but not in all.

In cases 1 and 2, a simultaneous (proportionate) rise in W_1 and W_2 – that is, with fixed W_2/W_1 - may either rise or increase the earnings ratio between the two individuals. It will rise in internal solutions for individuals of type 2, if in equilibrium 2´s labor supply is more elastic than 1´s. If 2´s equilibrium is at C, it will if the rate of change in H on 1´s indifference curve at C in response to the two changes is higher than 1´s labor supply elasticity.

We can devise other possible equilibria where wages paid differ from the exact marginal product of hours of each labor category, W_1 and W_2 above – maintaining total wage bill equal to total value product. In general, achievable separating equilibria could lead to a widening of the hourly wage gap as the average marginal product rises.

Labor supply arguments based on individual preferences under standard or fixed work-week arrangements explain that individuals that work beyond their preferred hours at a given wage will accept a lower wage for a freer hours choice – see for example, Altonji and Paxson (1988) and literature there cited; this would account for the empirical fact that hourly part-time payment is usually lower than the full-time wage rate. Our model would explain the separation of part-time and full-time contracts on the demand or production side, and is consistent with part-time work being associated to a lower hourly wage even under marginal product wage-setting. But, for the separating equilibrium of Fig. 2 (or 3) to be possible, the least productive workers must have a stronger relative preference for leisure relative to income than the others – the former choosing part-time contracts. Nevertheless, as noticed, a separating equilibrium with the opposite pattern would be possible – if, say, in, Fig. 2, B was to the left of D – the hourly wages required for a separating equilibrium would be decreasing in hours.

2.3. Strike Occurrence and Length: Strikes and "Walkouts"

Strike time is usually non-paid; and, from the worker´s point of view, it cannot be seen as leisure consumption – most strikes are accompanied by negotiating or demonstration efforts like picketing and others that require workplace attendance. Hence, it is reasonable to assume that striking "burns" time endowment, i.e., reduce T_i by the amount of strike length.

Graphically – see Fig. 5 -, striking translates into a shift of the individual b.c. to the right by the amount of time spent striking; denote it by s. Hours of work will be read in the graph as H_i minus the time he spends striking (or, horizontally, in the original b.c.).

Let an individual be at (or, rather, allowed to reach) his most preferred bundle at wage $\bar{W}$, which allows him to attain the utility level $\bar{U}$. He will only be interested in striking if, by striking, he can enjoy a higher utility level. We can define his willingness-to-strike curve as a relation between S and W, where W is the minimum wage that, associated with a loss of time endowment of size S, allows him to reach that utility level – the slope of the line that starts at S in the horizontal axis and is tangent to indifference curve $\bar{U}$. For a given individual, we can derive such function, $S = S(W, \bar{W})$, that is increasing in W (because indifference curves are convex) and decreasing in $\bar{W}$ (provided leisure is a normal good) [57].

[57] It would also be decreasing in exogenous non-labor earnings. For simplicity, we fix them to 0.

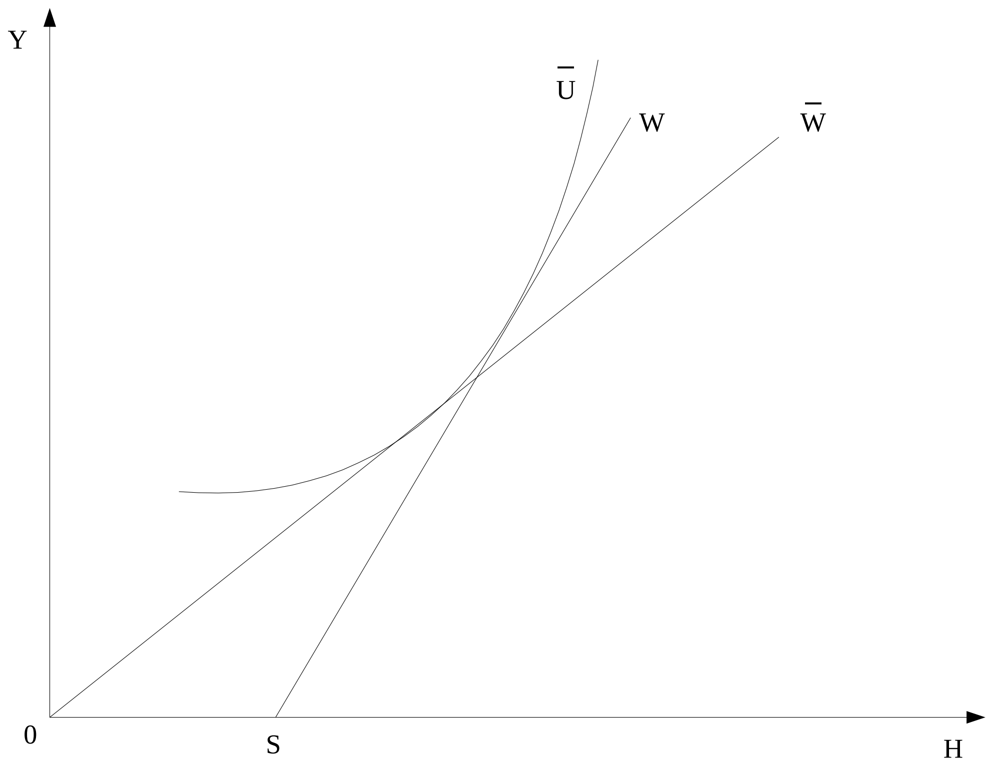

Fig. 5

An individual will only be interested in striking if and till the point that will allow him to reach the higher wage, W – that is $s \leq S(W, \bar{W})$. If he is on that function, he will consume less leisure and work fewer hours than in the original equilibrium (because indifference curves are convex).

This framework could explain worker mobility decisions. For instance, if search and adjustment costs to a new job are present, the function $S(W, \bar{W})$ represents the maximum amount of time loss an individual is willing to incur for a job yielding wage W when he has a job at wage $\bar{W}$. If we invert the function in order to W we get $W = W(S, \bar{W})$, increasing in both arguments, the minimum wage the worker of wage $\bar{W}$ demands to switch to another job that requires a time cost or loss of S.

Putting the two interpretations together, striking-cum-expected wage rise after strike has to allow a higher utility level than changing jobs, the “walkout” strategy – if the (subjective) costs of changing jobs increase with age, we would expect individual strike incidence to increase with age rather than looking for and switching to a higher paid job, the latter decreasing, both being able to represent a short-run disequilibrium signal to the employer of misalignment between the firm and market wages; both have to yield a higher utility than the current wage.

On the firm´s side there are also replacement costs to ponder in case of a walkout – that may be equivalent or lead to production delays as strikes imply; a game theoretical bargaining structure could explain strike occurrences in line with Wolinsky (2000) non-binding individual contracts model, allowing for multiple alternatives [58]. Or some "war of attrition" solutions where costs of delay (for the firm) can in some cases be interpreted as replacement costs.

2.4. Strikes with Adverse Selection and Moral Hazard.

1. If the firm cannot enforce or monitor hours beyond what workers really want to work (say, they will incur in absence), there will be no separating equilibrium. For instance in Case 1 above, worker of type 1 would choose the second wage and, ex-post, adjust hours at will.

Assume, however, that striking is an available "tool" in the following terms:

The firm offers two contracts, one at wage W_1 and another at wage W_2 if the worker strikes. In both contracts workers are allowed to choose hours.

A separating equilibrium may exist for a strike level s=S depicted in Figure 6, the interception of the line of slope W_2 that touches 1´s best indifference curve on his due b.c. It will exist, iff 2´s best bundle on that line is better than the one he can achieve at wage W_1 – a necessary condition is that such point lies (on SW_2 line) to the northeast of point P, the kink of the new overall budget constraint, OPW_2.

[58] Shaked and Sutton (1984) and Booth and Cressy (1990) include replacement as an option – but the former reach a no delay solution, in the latter two period model, replacement is just an end strategy.

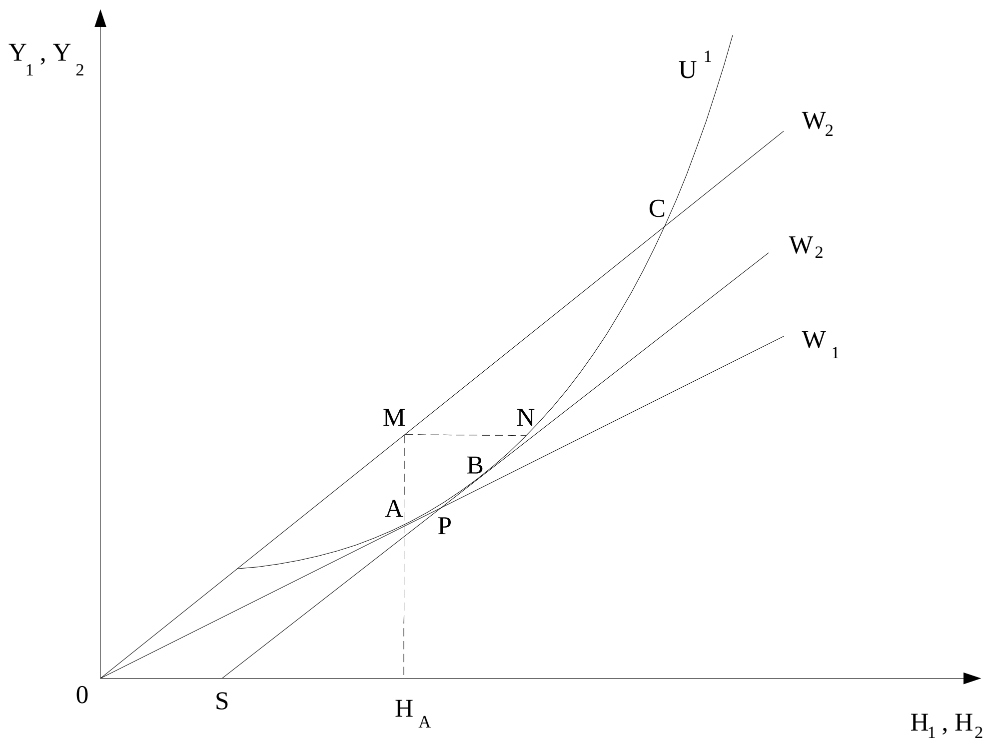

Fig. 6

(Minimum separating) Strike duration increases with W_2 because indifference curves are convex. It decreases with W_1 provided income is a normal good (hence, a rise in W_1 will allow a higher utility and indifference curve for 1; the new tangency of a W_2 line with the higher 1´s indifference curve will move upwards – to the northwest). That is, larger differences in productivity or worker heterogeneity imply higher separating strike length.

Provided that the high productivity workers are in a small proportion, and the average productivity wage does not allow type 2 workers to achieve a higher utility level than on the b.c. OPW_2, this schedule allows for the separating equilibrium to exist.

Other separating equilibria – with zero profits for the firms – with less strikes would be possible for a smaller wage gap if we relax the need for payment at marginal product.

2. Finally, striking may occur and allow for a separating equilibrium when firms must insure the same hours to both types of individuals.

In the previous examples we did not describe a "shirking" phenomena – we had "hidden information" but not "hidden action". It was never the case that ex-post hours of work were incorrectly accounted for but that, at worst, workers, at the agreed hourly wage contract, could adjust them at will. Consider, instead, one additional assumption with respect to available labor contracts: the employer can only monitor the same amount of (ex-post, i.e., deducted from strike length) hours for everybody (and these must be monitored). (Or team work is involved and must be accomplished simultaneously).

Then, for the case of Fig. 6 above, the strike length required for a separating equilibrium is MN, shorter than S, where N is the point on 1´s indifference curve that crosses A (his most preferred bundle at his productivity level) at income coordinate $W_2 H_A$. For such a separating equilibrium to exist, N must yield higher utility for individual of type 2 than the utility he gets at point A.

2 may be better or worse than when hours were allowed to differ. If hours are the same for everybody, the required strike length will decrease with W_1 and increase with W_2, and it is unclear how it responds to a proportionate increase of both wages – which, in any event, will not alter the relative earnings distribution, once hours are always the same for all workers.

Obviously, other contracts are possible, with the (common) hour settlement above type 1´s most preferred schedule at wage W_1 – again, this type of solutions would be ruled out if absenteeism is unavoidable; for a separating equilibrium to exist under such circumstances, 2´s most preferred bundle on the line $S´NW_2$ (not depicted: parallel to SW_2 and crossing point N) must be to the northeast of N.

3. Empirical implications of the models are difficult to distinguish. On the one hand, there are the main assumptions at stake; in fact sectors with:

- (industries with) larger firms and larger plants exhibit lower weekly hour dispersion (see Table B.20 in Appendix 2); sectors with a higher proportion of self-employment exhibit higher weekly hour dispersion (Table B.8 – PTCO refers to the proportion of not self-employed)

- (sectors with) larger plants suffer more from absenteeism (see correlations between DIMEST93 and HNAOT93 in Table B.25 of Appendix 2; the stronger positive correlations with plant size occur for absence due to work accidents and non-professional diseases.); sectors with a higher proportion of self-employment have less absenteeism (Table B.25 – even if correlations with PTCO are not significant)

This would suggest that it may be in fact more difficult for larger firms or plants - where monitoring may be more difficult and problems of asymmetric information more serious - to allow for flexible work-week contracts. Absenteeism, if non-paid by the firm, may be a device through each some flexibility is achieved ex-post [59].

Notice also that larger firms and larger plants rely less on part-time employment (the correlation between TRTNIPC and DIMEMP is –0.10942, and between TRTNIPC and DIMEST –0.053405), but the relation is not statistically significant: the lower dispersion effect encountered is not explained by the use of part-time work, but more uniform weekly hours assignment in both types of contracts.

However, overtime – paid with overtime premium – may be a device that discriminates worker times in the same (but opposite) manner as part-time, lowerly rewarded work: the correlations between TRTNIPC and TCEX, HEXTPTR and HEXTPC were –0.35065, -0.27710, -0.27174 (even if we could justify the negative sign by general hourly intensity requirements). Consistently, the correlations of TCEX, HEXTPTR and HEXTPC with DIMEMP were 0.30893, 0.12836, and 0.14485; and with DIMEST – being significant -, 0.55814, 0.138935, and 0.40273.

The second type of implications have to do with the main structure of the model: if in fact strikes occur when there are this type of asymmetric information problems, their incidence would be positively correlated to firm size [60] – which we already illustrated graphically and can be verified in Table B.18 for aggregate number of strikers and time loss, strikers per worker employed in the sector, and mean strike duration. And negatively related to self-employment – they usually are (see Table B.6), but the relation is not significant, and even positive with strike length.

More importantly, this type of asymmetric information stresses the strike as an individually driven occurrence rather than a block decision; that is, the relevant "bargaining unit" is an individual and not a union or a firm – the striker(s) rather than the strike(s) is the relevant dependent variable - individual employment rather than the collective contract, the latter being more in line with standard or (more) conventional bargaining models.

Finally, we have specific influences on the variables involved in the structure: a corollary is that if all firms face the same asymmetric information problems but for larger firms the need for a uniform workweek is more acute (or larger firms have additional problems of both types, which compound), then uniform workweeks would be consistent

[59] One could add that work-sharing in large firms allows absenteeism.

[60] Even if such relationship would also be found in other type of models of asymmetric information – see Gunderson, Kervin and Reid (1986), p. 261, for example. Also, industrialist school sociologists – see reference in Godard (1992) – would also advocate the same type of effect, with mass production and impersonal work relations of large firms and plants implying higher strike activity.

with lower strike incidence. However, non-uniform workweeks may just be a sign of non-existence of informational asymmetries either, and the reverse correlation may be encountered.

Also, the individuals who strike, are the higher productivity workers, the ones with higher ex-post opportunity cost of time and these must have indifference curves more to the right – i.e., they are the ones that prefer to work longer hours – have a stronger preference for income relative to leisure (or have a larger time endowment). Sectors with a higher proportion of high productivity workers would have more strikers but provided strikes can assure a separating equilibrium – and the existence of a separating equilibrium with strikes seems to require these in smaller proportions. It is difficult to measure workers productivity [61]; in Table B.15 of Appendix 2 we can see that the correlation between mean education attendance and individual strike activity (TGRPT and HGRPT) is positive, even if not statistically significant (positive and significant correlation is found with unionisation). A negative sign would, however, be reasonably explained by the interchange of signals, with more educated workers using education itself instead of strikes to signal – a la Spence – their higher productivity status. Tracy (1986) for the US finds, using data for 1973-1977, that "strike incidence is higher the more educated workers are, the younger they are, and the higher is the percentage of white workers"; Booth and Cressy (1990) for Britain, find a positive effect of proportion of skilled workers (they consider manual workers only) on strike probabilities; however, Ingram, Metcalf and Wadsworth (1993) find that manual workers are more strike-pron than non-manual workers.

Finally, part-time workers would more likely be the ones with lower hourly payment if strikes are being used as a signal and hours are freely chosen by workers; indeed - see Table B.7 – TRTNIPC and REMHOR, hourly wage, are strong and negatively correlated. On the other extreme, sectors with more intense use of overtime would have higher hourly base-wage: the correlation of TCEX, HEXTPTR and HEXTPC with REMHOR were – see Table B.10 – strong and positive [62].

4. Some comments can be added with respect to the role and industry pattern of self-employment. As argued in the literature, whenever informational asymmetries are high, the reliance on signals would be lower for self-employed – these individuals know

[61] Value added per worker is negatively correlated – see Table B.12. Yet, this must be explained by reasons other than informational asymmetries. Wages – see Table B.5 – are positively correlated with TGRPT and HGRPT.

[62] However, such positive correlation could also be implied by the existence of a direct relation between worker skills – hence hourly work value - and quasi-fixed labor costs, as is known in overtime demand theory.

their own characteristics and have no problem in setting their own schedule. That would be true for strikes, as remarked, but also for education [63] – in fact, the correlation between not self-employed and education is positive (see Table B16) [64].

Abstracting from strikes, from the first model of section 2.2, we concluded that in case 2 (and 1) a pattern of high wages-cum high hourly weekload might achieve separation, but also the reverse: high wages-cum low hourly weekload. Self-employed show higher weekly hours and lower wages and earnings; it may be the case that the impossibility of a separating contract for their preference-productivity mix would lead them to prefer self-employment – given that empirically, part-time contracts seem associated with lower wage rates, self-employed would be low productivity types with higher preference for income relative to leisure.

(Sectors of high self-employment show high employment growth and low overtime usage, and, as expected, low industry concentration, firm and plant size.)

3. Cross-Section Evidence.

3.1. Introduction.

1. It was the purpose of this section to search for the determinants of the Portuguese strike activity. We use sector means of a set of variables collected from official sources and described in appendix 1. We ended up with 30 observations, covering most of the sectors in the economy, for the year 1994 (and 1993, when lags or changes were required); we ignore multi-sector strikes [65].

Based on past literature, we believe that strike activity would be in part determined by:

- how much wages or wage growth are above the expectations, based on human capital and other skills enhancing labor productivity used in the sector, job characteristics, or even accepted traditional or historical industry differences in the market.

- particular institutional arrangements, including unionisation (TSIND)

- industry concentration (IG), leading to higher (abnormal) profits available for sharing with workers

[63] See Wolpin (1977), for example.

[64] But education and physical capital are claimed to be complements in production, with the latter more intensely used in larger firms – this would yield an alternative explanation.

[65] In 1994, 296 classical strikes were recorded out of public administration (30 classical strikes in public administration), involving 71129 workers and 78743 workdays loss (1,1 days of average strike duration). Only 4 (1,4%) strikes were multi-sector, involving 8516 (12,0%) workers and a loss of 3817 (4,8%) workdays.

- uncertainty or instability in the employment relation, either measured by the proportion of permanent contracts (PECCP) as by business cycle indicators (as the sector unemployment rate, TXDES; industry employment growth rate, DTCOCI).

- asymmetric information problems associated with firm size (DIMEMP) and weekly hours dispersion, as implied by the previous theoretical section, and also other indicators of hourly job intensity such as the proportion of partial time hours on the total hours worked in the sector (TRTNIPC).

2. A distinctive feature from other empirical research on strike activity is either the reliance on data sets where observation units are either collective contracts or negotiations. What we have is a yearly aggregate value of strike occurrences, of number of workers involved, and days lost per (two-digit) sector in the economy. Our data has the drawback of not allowing to study problems that have recently been focused such as holdout incidence and duration, or learning from previous strike experience...

But even with so little information on possible dependent variables, we still have alternatives. The choice of dependent variable is a problem that has already been focused on the literature: for instance, Dilt (1986) uses canonical correlation to compare the determinants of stock and flow measures (classified in the two groups, stock and flow, according to a special criterion) of aggregate strike activity – he finds different results for the two sets.

The first choice to be made is the relevant bargaining unit: if the bargaining units are the union (the set of employees) and the firm (in general, the employer block) – as most conventional bargaining models imply, being corporative in essence, specially those devoted to reproduce labor-management negotiations -, number of strikes would be the relevant dependent variable, and data would be supportive of a group bargaining model; a regression on total number of strikers would reveal the same pattern as a regression on strikes, with the same covariates appropriately scaled. Alternatively, if an asymmetric information model of the type of section 2 explains strike occurrence, then number of strikers (and total days lost) would be more relevant and the primary equation to specify [66]. Some crude tests were performed in the Appendix 3, and it would seem that strikes can have both group as individual explanations.

[66] Kaufman (1982) presents estimates of both strikes and strikers regressions. Some coefficients of the independent variables switch sign and significance from one type of regression to the other – but he does not explain the fact.

The second problem concerns aggregation. If the correct theoretical model focus on a decision unit – and the proper unit observation – as being union/firm or collective contract, then, with the micro data, binary choice models should be applied to the set of all firms or all contracts. With our data, at most we can construct average number of strikes per firm, an approximate figure for the frequency. If the decision unit is the individual, then the binary choice model should apply to strikers per - or, rather, out of - total employment (to individual contracts). Unfortunately we only have aggregate, by sector, data; should we explain total occurrences - strikes or strikers -, or frequencies – strikes per firm (once we have no indication of contracts at stake) or strikers per total employment? Moreover, and specially because we rely on cross-section sector data, we should control for sector size; should it be considered an independent variable in an aggregate - strikes or strikers - dependent variable formulation, or should we scale the explained variable and by what? Some tests are also preformed in Appendix 3.

A third issue deals with timing, which, as we use cross-section data and a fixed-period "flow" concept, may be less important. We implicitly assume that the contract length is the same in all sectors/individuals and that termination dates are uniformly distributed. Notice that if an individual strikes twice in a year – he is counted twice as a striker – that is because his problem is "doubled", which is reflected in the aggregate regressors [67].

3. We considered first the determinants of earnings and earnings growth. Secondly, we inspected the explanation of proportion of workers on strike, TGRPT, and average hours of strike per worker employed, HGRPT [68].

As most wage bargaining models suggest, sector strikes, as wages, may be determined by the same variables – in a reduced form equation; for some, the influence of the other variables would reverse as we go from wages to strikes, and the opposite relation between strikes and wages would, simultaneously, be observed say, low wages trigger high

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[67] Another advantage – or difference - of our approach is absence of censoring or truncation problems with respect to the sample: we are not restricting the subjects to contractual existence. That may explain the different effects found for some variables on strike activity, such as firm size – see Tracy (1987).

[68] We constructed the two variables using aggregate sector information on total strikers, and days lost and data on employment from Labor Ministry publications – se appendix 1 for details. Total coverage is not complete in that employment data – only around 2 million employees, when total employment, according to Employment Statistics, involved 4,4492 million people (4,6992 million jobs, 3,3597 paid jobs according to National Accounts) in 1994; we exclude from strikes data Public Administration, not covered in these statistics. Yet, it is possible that we overestimate sector probabilities (even if strike coverage may also be lacking some information), but hope that by a fixed proportion in all included observations in the cross-section analysis – as was suggested by the graphical analysis and comparisons in section 1.3.

strikes, strikes (through the other equation) set wages back up. A simultaneous equation model of strike incidence (and/or severeness) and wages could be conjectured instead: strike success has been modelled in such terms in recent studies [69]. However, the feedback sequence would eventually, require a lagged structure of influences – giving rise to a possibly not simultaneous system. In any event, on average in a single equation estimate, we would expect to capture a negative impact of wages on strike activity – that is, if strikes were required to achieve the average wage in the economy, that is because wages were lower in the sector during part of the year, suggesting that the average industry wage over the year in more strike inflicted sectors must be below average.

The study was conducted in such a way that a reduced form equation for strike variables was sought, and in a second stage, a residual – representing deviation of actual wage from expectations [70] – from sector wage regressions was additionally included. This required the previous performance of wage regressions. In these, we included variables that may be overly explaining wages for our purposes, and, may bias the significance of earnings residuals (or other wage variables) on strike equations towards zero: indirect wage effects may be captured in the explanatory variables - a problem which differs from simultaneity. On the other hand, effective wages are not the only bargained element – and effective earnings rather than only bargained floors, which we use as dependent variable, may be important to measure worker payment discontent; also for this reason, the significance of measured wage deviations from expected would not show up.

As suggested by previous tests – see Appendix 3 – we rely on weighted procedures, by TCOCI, total number of workers employed in the sector. This would also be advisable for a linear model designed for individual data when only individual averages are available.

3.2. Weighted Least Squares Linear Regressions

3.2.1 Earnings and Earnings Growth Regressions.

Some of the best weighted least squares regressions on monthly base earnings and earnings growth are presented in Table 6 below. Standard-errors are in curved brackets, p-values in square brackets.

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[69] See, for example, Card (1990b), Jimenez-Martin (1999), analysing Spanish wage settlements, Card and Olson (1995), studying 1880s strikes. Yet, on those papers the authors focus on wage increases rather than strikes and their causes; strikes are just instrumented in the equations.

[70] See Mauro (1982) and his footnote 17. He includes in the regressions the ratio of the firm´s wage to average industrial wage, expected to negatively explain strikes. We capture such divergence in the wage regression residuals, but corrected for industry-specific effects.

Our purpose was to obtain reasonable indicators of how actual earnings or earnings changes were below expectations – not so much to get at a definite explanation of each -, being measured by the corresponding regression residuals.

Education (EDUC) and age (IDAD) were included and have positive coefficients in the levels equation – age has a negative sign, however, in wage growth regressions -. Tenure (ANTIG) was discarded due to lack of significance Union density (TSIND) is available as an average over some years – we could not construct its change. TSIND shows high correlations with EDUC and IG, suggesting multicolinearity; its influence on wages was found negative and insignificant.

DIMEST, establishment size, turned out to be more relevant for sector wage level determination than firm size, DIMEMP – both and industry concentration, IG, are correlated -, which was discarded in these regressions.

Industry concentration, IG, turned out to be more significant in levels than in first differences in the earnings growth equation. As bargaining theory would suggest, the effect is positive – possibly reflecting larger profits being shared with workers.

Proportion of women employed in the sector decreases earnings – an increase in this proportion decreases wage growth.

Finally, hours of strike per worker in the previous year (1993) affected positively wage growth in plain least squares (from 1993 to 1994) but negatively with weighted least squares; its effect - neither lagged nor contemporaneous – did not show up in the earnings levels equation.

Table 6: Earnings and Earnings Growth Regressions
(Weighted Least Squares)

Independent Variables	REMBASE	REMBA93	Independent Variables	REMTC
CONSTANT	-23060.8 (21778.2) [0.300]	-10107.6 (20520.7) [0.627]	CONSTANT	6.34956 (1.18377) [0.000]
EDUC	12765.3 (1125.13) [0.000]	11967.5 (1110.43) [0.000]	DEDUC	5.88205 (2.96438) [0.059]
IDAD	1074.62 (629.718) [0.101]	746.344 (610.317) [0.233]	DIDADE	-1.12116 (0.587617) [0.069]
PCMQP	-445.064 (72.8143) [0.000]	-423.365 (69.9784) [0.000]	DPCMQP	-0.257948 (0.430749) [0.555]
IG	13797.6 (15118.6) [0.371]	22230.8 (14296.1) [0.133]	DIG	-2.82350 (21.7186) [0.898]
DIMEST	437.118 (218.700) [0.057]	168.246 (168.558) [0.328]	DDIMEST	-0.272082 (0.140044) [0.064]
			HGRPT93	-2.03703 (1.09628) [0.076]
Weight	TCOCI	TCOCI93		TCOCI
Residuals	RES1	RESL		RES2
SSE	0.728396E+14	0.62963E+14	SSE	0.560811E+7
RBAR2	0.981368	0.981137	RBAR2	0.820698
F-TEST	305.292 [0.000]	302.673 [0.000]	F-TEST	22.6702 [0.000]
White H.T.	29.6581 [0.330]	29.8560 [0.321]	L.M. het Test on Transform. Res.	0.227138 [0.634]
Log Likelihood	-470.339	-468.154	Log Likelihood	-224.646

We essayed the same regressions with the hourly wage rate, available for base earnings, and also for total monthly earnings. On the one hand, base earnings are usually negotiated, not total labor income; on the other, collective contracts and minimum wage legislation fix monthly (base) labor earnings, not hourly wages. Not surprisingly, therefore, the quality of the fit was worse for regressions in other labor income variables than those reported. Moreover, industry average workweek indicators were not significant when included in the REMBASE regressions – which did not occur in all of the other cases.

3.2.2. Strike Incidence and Severeness.

1. We considered the WLS (by TCOCI; number of workers in the each sector) and searched for a good model in the whole sample on the proportion of workers on strike, TGRPT, and striking hours per worker in the industry, HGRPT. Results are depicted in Table 7 below. The weighting by TCOCI seems to have dealt with heteroscedasticity and eight regressors were found important (statistics presented refer to the transformed model proper for ordinary least squares estimation).

From these results we conclude that

- industry concentration decreases sector strike frequency and length. This effect is opposite to the one found for wages; hence it reinforces the same phenomenon. Notice that industry concentration could promote unionisation or somehow a higher degree of bargaining/worker organization and promote strike activity [71]. It is particularly relevant that we find the opposite effect. This however, would be explained by oligopoly bargaining elements – see Feuss (1990), for example: in more competitive sectors, (general) strikes, by reducing output, increase prices, inducing the market into a rise in profits - only substantial strikes/output reductions would really (*ex post*) hurt profits; the required output reduction is, thus, much smaller in non-competitive sectors; consistently, less strike activity would be needed. Feuss concludes also that "the union must be able to remove more output (although a smaller percentage of output)" from large than small firms – the absolute effect would be consistent with larger firms requiring more strike activity, but not the relative effect – and this may be more adequate, once we explain relative strike frequencies; other explanations of the relation between firm size and strikes found below, would be required. Empirically, a negative effect of market share on (firm) strike activity and duration was found for Canada – see Godard (1992), even if he uses a small sample of firms: concentrated industries share abnormal profits with workers, an argument he traces back to

[71] Even if full centralization in wage bargaining is sometimes claimed not to promote unemployment and wage growth in the corporatist literature, being, therefore, implicitly, less prone to disruption. Nevertheless, that centralization in the bargaining process is easier or more likely in concentrated product markets is not a proven fact that we know of.

Galbraith (1969) –, but Tracy (1987) reports a positive effect of industry concentration for the U.S.

- union density favors strikes.

- job tenure length increases strike activity. Higher tenure may be associated to more specific human capital. On the one hand, it may imply higher workers´ relative strength in union bargaining, once dismissal is more difficult or costly for longer tenure workers; on the other, in theory, gains (and costs) of specific human capital are split between firms and workers – if this joint-investment is larger, there is a stronger incentive to bargain [72]. (Note that tenure and industry concentration effects have opposite signs – there is no "direct" splitting investment-cost in industry concentration.) Thirdly, and as advanced in section 2.3., changing jobs rather than striking for a given wage may be more costly for older workers – and tenure is positively correlated with age; hence, a positive influence, as encountered, would be reasonable as well.

- proportion of part time employment used in the sector increases strike activity.

- all else controlled for, strike intensity varies inversely with sector dynamism as measured by sector employment growth rate. If the sector is booming, it is likely that it is paying higher wages already – on the other hand, newly employed workers are not expected to strike, once their contract would just have been accorded and also they are more easily dismissed. If the industry is in a boom (relative to other sectors), individuals may be better, and enjoying a higher probability of success of obtaining an increase in wages and earnings by changing job (within the same sector) – i.e., it is worthwhile to incur costs of search and adjustment to move to another job rather than face strike costs; the argument would work in the opposite direction, however, with respect to changing sectors – implicitly, we are, or may be, finding this has high barriers.

- average firm size increases strike incidence and length. An explanation of strikes based on imperfect monitoring, akin to efficiency wage arguments, as we put forward in section 2 would suggest this effect. Gunderson, Kervin and Reid (1986) found a positive effect for Canada and, recently, Cramton and Tracy (1994) also report a positive effect for the US [73].

[72] Tracy (1987) justifies the negative impact he found for experience on the grounds of quasi-rents generated by specific human capital. As noted, an increase in the surplus bargained over implies opposite effects on strikes in different theories; Tracy´s finding justifies the joint cost hypothesis; ours, a model such as Booth and Cressy (1990). But, in any case, bargaining has only a meaning if such surplus exists.

[73] But Tracy (1986) found a negative one.

Table 7
(Weighted Least Squares: TCOCI)

Independent Variables	TGRPT	HGRPT
CONSTANT	-0.011686 (0.043929) [0.793]	-0.368721 (0.376765) [0.338]
IG	-0.189541 (0.105559) [0.086]	-1.54322 (0.919373) [0.107]
DIMEMP	0.000129405 (0.0000571375) [0.034]	0.00179736 (0.000493014) [0.001]
TSIND	0.00115325 (0.000474393) [0.024]	0.00672484 (0.00415976) [0.120]
DTCOCI	-0.00363087 (0.00156626) [0.030]	-0.023618 (0.014154) [0.109]
ANTIG	0.00747873 (0.00685522) [0.287]	0.101479 (0.059919) [0.104]
DANTIG	-0.086461 (0.035244) [0.023]	
DIDADE		-0.200314 (0.108207) [0.078]
TRTNIPC	0.00417714 (0.00238154) [0.093]	0.033472 (0.020832) [0.122]
SSE	2407.48	186026
RBAR2	0.491492	0.536992
F-TEST	4.95760 [0.002]	5.78798 [0.001]
L.M. het Test on Transformed Res.	0.012741 [0.910]	0.060045 [0.806]
Log Likelihood	-108.345	-173.555

2. The theoretical section pointed to the importance of hours – time allocation - indicators. In the first theoretical model, strike occurrence would be simultaneous to the hiring of both part and full time workers and in such model, required separating strike length was higher. This would explain a positive effect of TRTNIPC on HGRPT.

Yet, the existence of part-time employment might be the result of a lower incidence of monitoring problems that require inflexible work schedules – a negative sign would also be reasonable. (On the other hand, - the need for - its hiring may raise monitoring problems and hence, induce strike activity through the theoretical mechanisms described).

(We could think that the constraint of an equal workweek would be valid for all part-time workers - that is, the second class of models would apply for part-time employment only. The positive influence of TRTNIPC on strike incidence could, therefore, - more distantly - be associated with separating mechanism working only for part-time workers.)

TRTNIPC may also contain elements of job security: partial time contracts may be more volatile - and indeed the correlation between TRTNIPC and PECCP, the proportion of permanent contracts in the sector, is – 0.23806 – and the effect on strike activity of higher proportion of partial time employment may reflect higher job insecurity, and not only higher hourly flexibility; moreover it can reflect higher instability in the product market. Uncertainty is claimed to increase strike activity – from Hicks to Tracy (1987) [74] –, hence, to that extent, a positive sign would be expected. (A positive sign of TRTNIPC could also reflect worker dissatisfaction with job insecurity.) Moreover, within some theoretical models, the better the alternative available during the strike to the union, the higher its incidence [75]; if part-time jobs are an alternative that workers, during a strike [76], can resort to, then the sign found would also be justified.

Finally, a positive effect of TRTNIPC on strike regressions may just reflect general employment demands from workers.

As TRTNIPC would have mixed elements, we further regressed TGRPT and HGRPT on the above variables and, individually, one of several time indicators. These include the mean and dispersion indicators on hours worked, as well as some others,

[74] Tracy (1987) constructs much richer indicators of uncertainty about firm profitability, based on financial data. Unfortunately, we could not.

[75] Booth and Cressy (1990).

[76] This argument has been advanced before connected with the business cycle effect, supporting procyclicity. We believe that it is arguably applicable to Portuguese strikes.

collected for 1993, on absenteeism – both type of variables are described in the Appendix 1. We present the coefficients of the (individually) included variables in regressions of Table 7 on Table 8.

None of the inclusions turned out to be significant. Yet, the coefficients of both mean hours variables turned out to be positive, as well as the least insignificant coefficients of absenteeism indicators [77].

Table 8

Independent Variables	TGRPT	RBAR2	HGRPT	RBAR2
HCI	0.00651144 (0.00673692) [0.345]	0.491621	0.050448 (0.058924) [0.402]	0.532526
HCIVAR	0.000169550 (0.000820747) [0.838]	0.468368	-0.0000409017 (0.00718550) [0.996]	0.514945
HCISIG	0.00545794 (0.011610) [0.643]	0.472965	0.036283 (0.102282) [0.726]	0.517865
HCICV	0.129784 (0.397835) [0.747]	0.470059	0.435037 (3.47119) [0.901]	0.515293
HC	0.00698583 (0.00722113) [0.344]	0.492047	0.050451 (0.064949) [0.446]	0.529648
HCVAR	0.000951327 (0.00180588) [0.604]	0.474353	0.00323139 (0.016033) [0.842]	0.515902
HCSIG	0.00651684 (0.013577) [0.636]	0.473279	0.019031 (0.121297) [0.877]	0.515556
HCCV	0.175069 (0.486224) [0.722]	0.470633	0.224785 (4.33784) [0.959]	0.515012

[77] Dispersion indicators could reflect worker heterogeneity. In theoretical models, such as Booth and Cressy´s (through union´s alternative utility dispersion), it would increase strike frequency. But it may also render strike organization more difficult.

Table 8 (Cont.)				
Independent Variables	TGRPT	RBAR2	HGRPT	RBAR2
HNTCOCI	0.00546760 (0.00629049) [0.395]	0.487360	0.052330 (0.053936) [0.343]	0.537212
HNTCOC	0.0050232 (0.00670064) [0.462]	0.482766	0.047308 (0.058891) [0.431]	0.530559
HTTCOCI	0.00552712 (0.00554918) [0.331]	0.492790	0.048037 (0.047315) [0.322]	0.538995
HNAOT93	0.00296609 (0.00649296) [0.652]	0.473422	0.041288 (0.057254) [0.479]	0.527597
ANAAT93	0.035726 (0.041977) [0.404]	0.483399	0.123958 (0.372791) [0.743]	0.517161
ANADN93	0.0012177 (0.00973228) [0.902]	0.467847	0.036286 (0.085442) [0.675]	0.519382
ANADP93	-0.062814 (0.294185) [0.833]	0.468334	-0.602795 (2.60185) [0.819]	0.516175
ANASD93	0.636405 (0.623662) [0.319]	0.494989	2.60606 (5.93564) [0.665]	0.519816
ANAAI93	-0.012044 (0.094811) [0.900]	0.467438	0.470672 (0.833106) [0.578]	0.522822
ANAMP93	-0.019372 (0.048976) [0.696]	0.470677	0.064828 (0.449209) [0.887]	0.515541
ANAOC93	0.016420 (0.018558) [0.386]	0.489158	0.147564 (0.161810) [0.372]	0.535593

3. Finally, we included – one at a time – the residuals of Table 6 wage equations. Partial results are presented in Table 9.

A positive residual means an above average wage in the (own) industry. A sign of union-strikers (relative) justice or sensitivity to general earnings conditions would require us to find a negative impact of the residuals of the earnings regressions [78]. In other words, if an individual is already earning well, he is less willing to strike for a given achievable wage – this is implied by the willingness-to-strike interpretation given in section 2.3. The earnings regression residual can also be an inverse measure of the relative favorability of outside conditions – but, now, in outside sectors; for instance, in Tracy´s (1987) model, an improvement in union members´ outside opportunities would increase strike activity, which would imply a negative sign for the residuals´ coefficient. We consistently obtained the correct sign, but not significance. This may link to the discussion above of the effect of sector employment growth. We concluded there that barriers to sector change could be high – the interpretation of the wage in other sectors as a realistic alternative may be incorrect, hence the insignificant impact of the residuals (additionally, wages available in other sectors may be so only at the expense of some or more striking).

This, and the particular type of data we are using, led us to search for other specifications.

The share of wages out of total sector value added (REMVA) was also included, being its impact negative and significant [79] – sectors where the share of the pie captured by labor is already higher are less strike-prone [80], which is consistent with Booth and Cressy (1990)´s model where "strike probabilities increase with the surplus to be bargained over", if we admit that such surplus is inversely related to the wage bill share. The change from

[78] The inspection of the effect of the residual of the previous year wage equation allows us to effectively distinguish the interpretation from the view of the literature on the effect of strikes on wage settlements. Nevertheless, with respect to earnings growth residual, the negative effect can distantly be connected with the negative effect of real wage change during prior contracts on strike probabilities found in Cramton and Tracy (1994).

[79] In the second part of Table 5.1, we found a negative relation (even if not statistically significant) between strike time series, and the weight of the wage bill share out of GDP and real wage cost indicators. Somehow, that relation would be here recaptured for cross-section data. Nevertheless – see Appendices A and B –, the negative observation of REMVA in the cross-section sample may be biasing the conclusions, once without it, the simple correlation of REMVA with strike incidence – see Table B12 of Appendix B - becomes positive, even if insignificant.

[80] Simultaneity issues are particularly important in interpreting the impact of wage-related variables. We cannot help to remind that Ashenfelter and Johnson (1969) predict that "the parties were more likely to agree the greater is the ratio of the preagreement profit level to the wage bill", which would seem in contrast with the evidence we found – nevertheless, we are not necessarily measuring pre-agreement patterns: Farber (1978) posits a negative relation between labor share and the rate of concession or decay of union´s wage demands an increase of which increases strike likeliness according to A&J.

93 to 94, was positive and (less) significant, which just may indicate the role of both 94 and 93 levels of the wage bill share in determining the strike pattern.

Table 9

Independent Variables	TGRPT	RBAR2	HGRPT	RBAR2
REMVA	-0.0000548164 (0.0000237496) [0.031]	0.573264	-0.000473818 (0.000209905) [0.035]	0.608926
DREMVA	0.000309480 (0.000153451) [0.057]	0.552212	0.00263857 (0.00136370) [0.067]	0.587615
RES1	-0.00000121724 (0.00000138903) [0.391]	0.487059	-0.00000756744 (0.0000123125) [0.545]	0.523836
RESL	-0.00000101772 (0.00000141739) [0.481]	0.480332	-0.00000622449 (0.0000125299) [0.625]	0.520643
RES2	-0.00305628 (0.00503749) [0.551]	0.476172	-0.010660 (0.044898) [0.815]	0.516178
DRES = RES1 - RESL	-0.00000387194 (0.00000576142) [0.509]	0.480635	-0.0000261098 (0.0000511697) [0.615]	0.521797
RES1	-0.00000415319 (0.00000583356) [0.485]	0.470357	-0.0000278099 (0.0000521839) [0.600]	0.504783
RESL	0.00000307001 (0.00000591806) [0.610]		0.0000211594 (0.0000529425) [0.694]	
RES1	-0.00000155729 (0.00000753656) [0.838]	0.449482	-0.0000229871 (0.0000676222) [0.738]	0.478815
RESL	0.000000151225 (0.00000797022) [0.985]		0.0000157315 (0.0000714994) [0.828]	
RES2	-0.00388913 (0.00695614) [0.583]		-0.00729068 (0.062481) [0.908]	

3.2.3. Strikes, the Industry (Business) Cycle and Production Frontier

The business cycle influence in time series research is sometimes proxied by a residual of employment regressions on trend and trend squared – other studies use the industrial production regression residuals, others unemployment rates, degree of capacity utilization. As we are in a cross section, we must redefine the concept or the effect we are measuring. Additionally, we rely in a very small sample, hence, multicolinearity among the several indicators is to be expected. We therefore chose to include and report several alternative indicators one at a time.

Industry employment growth was the measure of industry dynamism used in the previous empirical section. We considered below the inclusion of industry cycle indicators: growth rate of gross value added (VABTC), and of effective (gross) production (PEFTC).

We also decomposed both nominal growth rates, in real growth (VABRTC and PEFRTC) and price changes (VABPTC and PEFPTC). To some extent, we would expect the impact of real growth rates to be similar to those of the employment growth rate; alternatively, including both employment and real production or output growth could control for productivity gains explaining earnings growth rates, for example, and, indirectly, strikes.

Note that strikes, by reducing yearly production, may increase output prices – if a positive effect of price change indicators is to be found, it may be partly explained by endogeneity. A negative effect could not be so attributed to reverse causation: then we could read "low prices, low wages, high discontent".

Some of these indicators may just reflect industry production modes – for example, REMVA above, or the use intensity of overtime employment - that may affect one way or another the perceived effectiveness of a strike movement, through mechanisms not captured in the other variables.

1. Firstly, the indicators were included in the wage regressions – see Table 10. They are consistently positive but strongly insignificant, with the exception of the sector unemployment rate – which is significantly (and positively – it would be an inverse indicator of sector expansion) related to mean sector earnings. Yet, the positive sign of unemployment could be explained as hedonic payment practices for unemployment risk.

Table 10

Independent Variables	REMBASE	RBAR2	REMTC	RBAR2
VABT	-0.111212 (0.722604) [0.879]	0.980590	-0.000069505 (0.00020068) [0.732]	0.814255
VABTE	-0.202637 (0.489309) [0.683]	0.980752	-0.000239771 (0.000140656) [0.102]	0.840185
VABTTC	-123.447 (74.1125) [0.109]	0.982768	0.00720872 (0.022989) [0.757]	0.812867
VABTTEC	-118.181 (74.0384) [0.124]	0.982584	0.010070 (0.022526) [0.659]	0.813524
VABRTTC	-115.958 (74.7919) [0.135]	0.982403	0.00075117 (0.024392) [0.976]	0.812532
VABRTET	-112.295 (75.1092) [0.148]	0.982271	0.00378094 (0.023858) [0.876]	0.812641
TXDES	1595.66 (650.016) [0.022]	0.984705	-0.249137 (0.211656) [0.252]	0.822052
TCEX	-41.9191 (279.506) [0.882]	0.980568	-0.072317 (0.109948) [0.518]	0.817420
HEXTPC	-285.349 (1655.56) [0.865]	0.980575	-0.821869 (0.816432) [0.325]	0.823746
HEXTPTR	-624.380 (3979.70) [0.877]	0.980571	-2.14290 (1.97689) [0.290]	0.824899

Table 10 (Cont.)

Independent Variables	REMBASE	RBAR2	REMTC	RBAR2
PEFTC	-130.456 (108.294) [0.241]	0.981807	-0.00699436 (0.032349) [0.831]	0.813275
VABTC	-117.824 (74.3966) [0.127]	0.982585	0.00553111 (0.022861) [0.811]	0.812658
PINTC	6.05150 (180.060) [0.973]	0.980557	-0.075468 (0.046224) [0.117]	0.833971
PEFPTC	-93.9481 (328.767) [0.778]	0.980651	0.025644 (0.102642) [0.805]	0.812858
VABPTC	21.2295 (140.839) [0.881]	0.980558	0.024403 (0.042103) [0.568]	0.814230
PINPTC	-360.587 (863.171) [0.680]	0.980760	0.081702 (0.218445) [0.712]	0.813826
PEFRTC	-99.9377 (103.793) [0.346]	0.981348	-0.00973649 (0.031931) [0.763]	0.813676
VABRTC	-109.990 (74.7760) [0.155]	0.982239	-0.000703650 (0.024139) [0.977]	0.812576
PINRTC	22.7904 (195.614) [0.908]	0.980566	-0.097196 (0.051044) [0.070]	0.840574
PEFPTC	-449.144 (404.743) [0.279]	0.981768	0.013791 (0.119708) [0.909]	0.804721
PEFRTC	-187.737 (130.098) [0.163]		-0.00767160 (0.037265) [0.839]	
VABPTC	-60.6985 (147.777) [0.685]	0.981648	0.025324 (0.044133) [0.572]	0.805368
VABRTC	-122.497 (82.0270) [0.150]		0.00241791 (0.025112) [0.924]	
PINPTC	-365.827 (883.100) [0.683]	0.979896	0.151014 (0.208236) [0.476]	0.837411
PINRTC	26.4825 (199.434) [0.896]		-0.103582 (0.052349) [0.061]	

At the 5% level, further effects of the sector demand dynamism seem absent – even if usually negative as expected. Yet some competition with/substitution by intermediate products may be in effect: an increase in real usage of intermediate products depresses labor productivity and mean sector wage growth.

2. In Table 11, we present the analogous estimates for strike regressions. The general pattern suggests:

- the output cycle indicators - growth rates of production, gross value-added nominal, real, or corresponding prices (second part of Table 11) - are usually insignificant (production price changes is the only exhibiting negative impact on strikes).

- overtime usage, however, has a positive effect but not significant

(The latter could be related to reaction to time allocation practices in line with our theoretical arguments of section 2. Also, to higher quasi-fixed labor costs, and larger specific human capital)

Unemployment rate has a positive effect, but not significant. Even if evidence is usually statistically irrelevant, the signs of the coefficients show a tendency for output related indicators to be positive and employment to be negative (with unemployment rates having a positive effect). In terms of usual theories, two different elements of the cycle are important in determining strike proneness: one is outside opportunities (alternative wages), which, in general, increase strikes; then, to the extent that higher sector unemployment rates reflect lower alternatives – as Card (1990b) interprets -, a negative coefficient is to be expected; but in those models, immediate "walkout" of workers instead of a strike is not contemplated, which could explain a positive impact of unemployment, as advanced for the negative sign found for DTCOCI. The other element is "inside" profitability or rents, a raise of which implies a decrease in strike activity in models such as Reder and Neuman´s (1980) joint cost hypothesis, Tracy (1987) or Card (1990b), but an increase in models such as Booth and Cressy (1990). A positive coefficient of output related indicators could be linked to the latter.

Table 11

Independent Variables	TGRPT	RBAR2	HGRPT	RBAR2
VABT	-0.0000106022 (0.00000413079) [0.018]	0.598304	-0.000104301 (0.0000410016) [0.019]	0.631685
VABTE	-0.00000565452 (0.00000291834) [0.066]	0.552371	-0.0000544723 (0.0000282161) [0.067]	0.591024
VABTTC	0.00015787 (0.000527415) [0.768]	0.469392	0.00460760 (0.00478215) [0.346]	0.535241
VABTTEC	-0.0000133426 (0.000523526) [0.980]	0.929388	0.00299512 (0.00480644) [0.540]	0.523621
VABRTTC	-0.000100496 (0.000502606) [0.843]	0.468241	0.00229667 (0.00472993) [0.632]	0.520513
VABRTET	-0.000244762 (0.000501932) [0.631]	0.473127	0.000938727 (0.00476953) [0.846]	0.515922
TXDES	0.00506913 (0.00411866) [0.232]	0.503600	0.053912 (0.034017) [0.128]	0.567882
TCEX	0.00189557 (0.00157338) [0.242]	0.501219	0.012445 (0.013105) [0.353]	0.535316
HEXTPC	0.00915826 (0.00925041) [0.333]	0.490896	0.058173 (0.080494) [0.478]	0.526935
HEXTPTR	0.022953 (0.022458) [0.318]	0.492494	0.141564 (0.195356) [0.477]	0.527035

Table 11 (Cont.)				
Independent Variables	TGRPT	RBAR2	HGRPT	RBAR2
PEFTC	0.00106158 (0.000729914) [0.161]	0.515814	0.013827 (0.00634192) [0.041]	0.604223
VABTC	0.000137301 (0.000532235) [0.799]	0.468874	0.00487087 (0.00480087) [0.322]	0.537413
PINTC	0.00316113 (0.00108587) [0.008]	0.620966	0.021752 (0.010115) [0.043]	0.602147
PEFPTC	-0.00267718 (0.00181438) [0.155]	0.518449	-0.029903 (0.015158) [0.062]	0.593095
VABPTC	0.000866293 (0.000786775) [0.283]	0.494852	0.00587867 (0.00702608) [0.412]	0.529838
PINPTC	0.00558181 (0.00461400) [0.240]	0.502380	0.027662 (0.040596) [0.503]	0.525270
PEFRTC	0.000991121 (0.000656462) [0.146]	0.519549	0.013484 (0.00569655) [0.028]	0.617442
VABRTC	-0.000108326 (0.000503608) [0.832]	0.468370	0.00261424 (0.00472679) [0.586]	0.522145
PINRTC	0.00308093 (0.00122501) [0.020]	0.590907	0.022597 (0.011241) [0.057]	0.593009
PEFPTC	-0.00146033 (0.00269278) [0.594]	0.503420	-0.011672 (0.020362) [0.573]	0.605560
PEFRTC	0.000604793 (0.000976424) [0.543]		0.010394 (0.00791067) [0.204]	
VABPTC	0.00102610 (0.000920959) [0.278]	0.472790	0.00955769 (0.0078424) [0.237]	0.531878
VABRTC	0.000203891 (0.000573817) [0.726]		0.00547053 (0.00522790) [0.308]	
PINPTC	0.00593808 (0.00407842) [0.161]	0.612090	0.027674 (0.038012) [0.475]	0.583559
PINRTC	0.00313872 (0.00119426) [0.016]		0.022599 (0.011369) [0.061]	

The regressions including the growth rate of intermediate products (materials and energy) originate the best fit, as well as value added per worker. The impact of the materials value growth rate on strike activity is positive. This could be explained as follows: a rise in the value of other inputs used in production decreases both worker and employer share (the cake to be shared) and elicits disruption. The finding is also consistent with the not novel argument of the impact of the "costs of strikes" on strike activity, and with costs of strike varying inversely with the substitutability between labor and other inputs [81]. If substitution in production by other inputs is possible and being accomplished, the relative opportunity cost (the eventual pie loss) of (only) labor not working is lower; hence, the overall costs of striking decrease – implying an increase in observed strike activity. (The possible negative effect of strikes on upstream markets has been noticed before: Persons (1995), with respect to intermediate products (steel) in the automobile market, concludes that strikes affected negatively steel suppliers of automobile struck companies – our reasoning would predict such effect for complement inputs.)

At first glance, the result found for the value-added per worker coefficient would seem inconsistent with the theoretical models of section 2, in which more productive individuals are the ones that strike. Yet, as was pointed out, higher value-added yielding workers may chose other signalling devices, namely, education – education or training would promote worker productivity on the one-hand and, partly and more conveniently provide the required signal.

Additionally, higher value-added per worker may, in part, reflect higher capital intensity. Tracy (1987) and Cramton and Tracy (1994) report an insignificant (positive more than negative) influence of the capital-labor ratio on strike occurrences. Ingram, Metcalf and Wadsworth (1993) find that "bargaining groups in firms in which labor costs are a high fraction of total costs are less likely to go on a strike than ones operating in a more capital-intensive environment" – they justify the sign found REMVA on strike equations of the previous sub-section. But, their finding and interpretation would not be consistent with the sign we found for value added per worker, higher in more capital-intensive sectors.

[81] Reder and Neumann (1980) invoke this type of mechanism with respect to the ease of intertemporal substitution in production reducing costs of strike, illustrated empirically by the positive effect of inventory fluctuations on strike activity.

Thirdly, more productive sectors would pay higher wages – we found no evidence of that in the wage equations above, but their dependent variable are base full time wages -, consistent with lower strike activity. (Also, even if not significant, coefficients of measures based on the change of value added per worker also have a negative sign on strike incidence, even if not significant.)

We present in Table 12 strike incidence and severeness equations with all the previous regressors and both value-added per worker and intermediate product growth rates.

The main effect of the inclusion of these indicators was the loss of significance of industry concentration (IG) in the regression – even if its t-ratios remained larger than one. A possible interpretation is that value-added per worker may be higher in more capital-intensive sectors, these being more highly concentrated industries – the three conditions would thus detain strike activity; colinearity among them would reduce the significance of one of them when the other is controlled for. (In fact, the simple correlation coefficient between VABT and IG is 0,46568. The correlation of REMVA with IG is –0,17208 and with VABT 0,20731 – that is, both are small.)

Table 12 (Weighted Least Squares: TCOCI)		
Independent Variables	TGRPT	HGRPT
CONSTANT	-0.089958 (0.037802) [0.027]	-0.803752 (0.376792) [0.045]
IG	-0.100973 (0.080433) [0.224]	-0.879780 (0.776140) [0.270]
DIMEMP	0.000140118 (0.0000423603) [0.004]	0.00195669 (0.000412556) [0.000]
TSIND	0.000705182 (0.000398207) [0.092]	0.00474076 (0.00389065) [0.237]
DTCOCI	-0.00293640 (0.00132542) [0.038]	-0.017143 (0.012836) [0.197]
ANTIG	0.013102 (0.00528689) [0.022]	0.135406 (0.049983) [0.014]
DANTIG	-0.085548 (0.027236) [0.005]	
DIDADE		-0.089049 (0.103439) [0.400]
TRTNIPC	0.00445424 (0.00178219) [0.021]	0.032374 (0.017526) [0.080]
VABT	-0.0000101259 (0.00000341659) [0.008]	-0.0000986776 (0.0000376014) [0.016]
PINTC	0.00304415 (0.000928337) [0.004]	0.020192 (0.00895872) [0.036]
SSE	1191.83	113401
RBAR2	0.727263	0.691150
F-TEST	9.34746 [0.000]	8.37122 [0.000]
LM het test	0.00195008 [0.965]	0.237877 [0.626]
Log Likelihood	-97.7989	-166.131

4. Limited Dependent Variable Models

4.1. The Linear Probability Model

A. The Model

1. The study of individual strike data usually casts a binary choice model.

We have n_i individuals (draws) for each sector i, out of a total of m sectors. $TGRPT_{ti}$ is 1 if the individual/worker t in sector i engaged in a strike, 0 if not. Consider that each observation is the result of a random draw experience from a binomial distribution (family) with parameter p_{ti}, which is a (linear) function of individual characteristics, that is

(1) $$TGRPT_{ti} \sim b(p_{ti}, 1) \quad t = 1, 2, \ldots, n_i \ ; \ i = 1, 2, \ldots, m$$

and

(2) $$p_{ti} = \beta' X_{ti} \ , \quad t = 1, 2, \ldots, n_i \ ; \ i = 1, 2, \ldots, m$$

where X_{ti} is a (column) vector of k individual characteristics and β a (column) vector of k parameters, which is our purpose to estimate. The maximum likelihood estimator would solve

$$\underset{\beta}{Max} \sum_{i=1}^{m} \sum_{t=1}^{n_i} TGRPT_{ti} \log(\beta' X_{ti}) + (1 - TGRPT_{ti}) \log(1 - \beta' X_{ti})$$

Applying OLS to

(3) $$TGRPT_{ti} = \beta' X_{ti} + \varepsilon_{ti} \quad t = 1, 2, \ldots, n_i \ ; \ i = 1, 2, \ldots, m$$

yields different estimators, but stands as a viable procedure with the known shortcomings: ε_{ti} can only take two values, as usually discussed in textbooks, and it does not have constant variance; as such, the application of least squares to (3) would yield unbiased and consistent estimators for β, even if not efficient <u>if</u> the structure is really (3).

However, we are not assuming (3), but rather using it to estimate the parameters of an underlying Bernoulli distribution function, i.e., the parameters of (2). It is shown below that OLS may have its appeal.

We have an additional complication: we only have mean (grouped) data. We observe

$$\text{TGRPT}_i = \sum_{t=1}^{n_i} \frac{TGRPT_{ti}}{n_i} \quad ; \qquad \text{X}_i = \sum_{t=1}^{n_i} \frac{X_{ti}}{n_i}$$

If we average the left and right hand-sides of (3) we arrive at:

$$(4) \qquad \text{TGRPT}_i = \beta' \text{X}_i + \varepsilon_i \quad i = 1, 2, \ldots, m, \quad \text{where} \quad \varepsilon_i = \sum_{t=1}^{n_i} \frac{\varepsilon_{ti}}{n_i}$$

Whatever $\text{Var}(\varepsilon_{ti})$ is, if it is constant and errors are independent across individuals,

$$(5) \qquad \text{Var}(\varepsilon_i) = \frac{Var(\varepsilon_{ti})}{n_i}$$

The transformation of (4) to correct for this type heteroscedasticity is equivalent to the application of weighted least squares by the variable that contains n_i. It is also equivalent to the application of straight least squares to the transformed model:

$$(6) \qquad \sqrt{n_i}\ \text{TGRPT}_i = \beta' \text{X}_i \sqrt{n_i} + \nu_i \quad ; \quad i = 1, 2, \ldots, m$$

with, implicitly, $\nu_i = \varepsilon_i \sqrt{n_i}$ and $\text{Var}(\nu_i) = \text{Var}(\varepsilon_{ti})$.

That $\text{Var}(\varepsilon_{ti})$ is constant, is arguable as stated before. Nevertheless the weighting by n_i apparently improves OLS.

The weighted (by TCOCI) least squares regressions on TGRPT_i, recommended by the regressions on the OLS squared residuals presented in Appendix 3, may, thus, be interpreted as (6).

More distantly, if we consider HGRPC_{ti} is a draw from one work day in the industry, regressions on HGRPC_i, provided the yearly number of workdays is constant across sectors, could have a similar binomial justification – even if HGRPC_i would more adequately be days of strike over work days plus days of strike and not only days of strike over work days.

Results of heteroscedasticity tests were presented and the null was usually not rejected – which somehow allows us to rely on the coefficient significances found.

2.1. Suppose we are just measuring strike frequency and that individual characteristics are irrelevant. Then the special case of the previous experiment is just:

(7) $TGRPT_{ti} \sim b(p, 1) \quad t = 1, 2, \ldots, n_i \; ; \; i = 1, 2, \ldots, m$

Then the maximum likelihood estimator for p is:

(8) $$\hat{p} = \sum_{i=1}^{m} \sum_{t=1}^{n_i} \frac{TGRPT_{ti}}{n} \quad \text{where} \quad n = \sum_{i=1}^{m} n_i$$

$\hat{p}$ is an unbiased estimator of p, with variance $\frac{p(1-p)}{n}$, equal to the Cramer-Rao lower bound – see, for instance, Johnson and Kotz (1969).

Let us consider using least squares to estimate p. If we specify:

(9) $TGRPT_{ti} = p + \varepsilon_{ti} \quad t = 1, 2, \ldots, n_i \; ; \; i = 1, 2, \ldots, m$

it is easy to show that the least squares estimator for p is (1). Also:

(10) $$\hat{Var}(\varepsilon_{ti}) = \frac{n}{n-1} \hat{p} (1 - \hat{p}) \quad \text{and}$$

(11) $$\hat{Var}(\hat{p}) = \frac{1}{n-1} \hat{p} (1 - \hat{p})$$

2.2. We only have data on $TGRPT_i = \sum_{t=1}^{n_i} \frac{TGRPT_{ti}}{n_i}$. Nevertheless, p can be adequately and equally be estimated using:

(12) $$\hat{p} = \sum_{i=1}^{m} TGRPT_i \frac{n_i}{n}$$

Let us average the left and right hand-sides of (3) over t. Then:

$$\text{(13)} \qquad TGRPT_i = p + \varepsilon_i \quad i = 1, 2, \ldots, m, \quad \text{where} \quad \varepsilon_i = \sum_{t=1}^{n_i} \frac{\varepsilon_{ti}}{n_i}$$

The application of straight least squares to the transformed model:

$$\text{(14)} \qquad \sqrt{n_i}\ TGRPT_i = p\ \sqrt{n_i} + \nu_i \quad ; \quad i = 1, 2, \ldots, m$$

originates a $\hat{p}$ equal to (8) – and (12). However the least squares estimator of the variances are different:

$$\text{(15)} \qquad \widehat{Var}(\nu_i) = \frac{\sum_{i=1}^{m} n_i TGRPT_i^2 - \hat{p}\sum_{i=1}^{m} n_i TGRPT_i}{m-1} \neq$$

$$\neq \frac{\sum_{i=1}^{m}\sum_{t=1}^{n_i} TGRPT_{ti}^2 - \hat{p}\sum_{i=1}^{m}\sum_{t=1}^{n_i} TGRPT_{ti}}{n-1} = \frac{n}{n-1}\ \hat{p}\,(1 - \hat{p})$$

and

$$\text{(16)} \qquad \widehat{Var}(\hat{p}) = \frac{1}{n}\ \widehat{Var}(\nu_i)$$

Even if we had grouped data/observations and in each group i only 1´s or 0´s were present, the estimator of the variance of $\hat{p}$ in (11) would only be recovered multiplying the one now obtained by $\frac{m-1}{n-1}$.

B. Sector Selection: A Simple Specification Test and Some Estimates

1. As we are dealing with a sample where some sectors do not exhibit any strike activity at all – TGRPT and HGRPT are 0 for seven observations –, it is reasonable to inquire whether these are generated by a different process than the others. As such, we started by repeating the regressions for the remaining 24 observations. We did it including

isolated dummies for each of the seven sectors for which there are no reported strikes; the coefficient estimates and other regression results are in Table 13; we present in the last row the corresponding Chow test for their joint significance.

In regressions with these variables, the dummies were usually individually insignificant at the 5% level – sector 24, Banking and Other Monetary and Financial Institutions, was the sole exception -, and the joint (reported) F test for its removal was not rejected.

Table 13				
Independent Variables	TGRPT	TGRPT	HGRPT	HGRPT
DU1	-10.5486 (13.0516) [0.432]	-4.38257 (12.2230) [0.726]	-64.8214 (111.742) [0.570]	-63.0719 (119.156) [0.606]
DU3	-3.99298 (10.8372) [0.718]	-1.63134 (9.33021) [0.864]	-15.0467 (91.3783) [0.871]	-2.94229 (88.9027) [0.974]
DU4	1.77277 (10.9078) [0.873]	0.839147 (9.35185) [0.930]	-11.1184 (91.0418) [0.904]	-20.7904 (88.1578) [0.817]
DU5	-1.47926 (11.0228) [0.895]	-1.42867 (9.48269) [0.883]	-22.2733 (93.2000) [0.814]	-14.1593 (90.6557) [0.878]
DU6	2.51481 (11.0615) [0.823]	3.00189 (9.56317) [0.759]	-21.8638 (91.7297) [0.815]	-24.2634 (88.8537) [0.789]
DU17	0.052085 (10.9990) [0.996]	3.60432 (9.52087) [0.711]	-31.1682 (92.1336) [0.740]	-1.30178 (91.3560) [0.989]
DU24	-28.8872 (15.0068) [0.073]	-10.5660 (14.5353) [0.480]	-303.486 (130.112) [0.034]	-147.404 (154.577) [0.358]
SSE	1727.73	1098.36	123567	99972.6
RBAR2	0.467436	0.612630	0.555818	0.585881
F-TEST	2.77658 [0.030]	3.77766 [0.010]	3.51211 [0.011]	3.48368 [0.014]
Log Likelihood	-103.369	-96.5738	-167.418	-164.240
CHOW F-TEST	0.84308527 [0.56953]	0.15804453 [0.98962]	1.0831381 [0.42056]	0.24945738 [0.96336]

2. Given the nature of the – limited - dependent variables, a natural extension of it would entail the specification of a TOBIT for TGRPT and a Sample Selection model for both equations - in TGRPT and HGRPT.

We present some of the results below, as well as of the following PROBIT´s:

$$(17)\quad \text{Log L} = \sum_{i=1}^{30} [\text{TGRPT1}_i \log\Phi(\beta' X_i) + (1 - \text{TGRPT1}_i) \log\Phi(-\beta' X_i)]$$

$$(18)\quad \text{Log L} = \sum_{i=1}^{30} [\text{TGRPT1}_i \log\Phi(\beta' \sqrt{n_i}\, X_i) + (1 - \text{TGRPT1}_i) \log\Phi(-\beta' \sqrt{n_i}\, X_i)]$$

where $\text{TGRPT1}_i = \begin{cases} 1 \text{ if } \text{TGRPT}_i > 0 \\ 0 \text{ if } \text{TGRPT}_i = 0 \end{cases}$

and n_i represents the number of workers in industry i (TCOCI_i). $\Phi(.)$ denotes the cumulative standard normal distribution function. Specification (18) can be justified by the fact that $\text{Var}(\varepsilon_i)$ must be proportional to $\frac{1}{n_i}$; hence an adequate weighting of the distribution is required.

We only have seven zero observations – which restricts the number of regressors used; we started by selecting some of the above and estimated versions (17) and (18); standard-errors were quite high when computed by Newton´s second derivatives method; Eicker-White [82] standard-errors on the same estimates turned out to be much lower and are the ones reported for those versions. We then proceeded, on a sort of backward stepwise selection, to restrict both models (we were guided by Newton´s t-statistics); the best PROBIT´s found from the above set of regressors are presented below, (17A) and (18A):

[82] White´s (1982) estimator is robust to mispecification such as heteroscedasticity but in some cases underestimates the variance. See Greene (2000), p. 823-824; also, p. 491.

Table 14

Independent Variables	(17) E-W	(17A)	Marginal Effects	(18) W E-W	(18A) W	Marginal Effects
CONSTANT	-2.88057 (2.96805) [0.332]	1.24444 (0.879374) [0.157]	0.106245 (0.114474) [0.353]	-0.055508 (0.033630) [0.099]	-0.0023696 (0.00679372) [0.727]	-0.0000198225 (0.0000806765) [0.806]
IG	-8.89375 (5.04153) [0.078]	-5.44712 (2.59997) [0.036]	-0.465052 (0.396309) [0.241]	-0.044675 (0.017795) [0.012]	-0.00512210 (0.00811780) [0.528]	-0.0000428480 (0.000145186) [0.768]
PINTC	0.256826 (0.098099) [0.009]	0.169879 (0.076050) [0.025]	0.0145035 (0.0120607) [0.229]	0.00294029 (0.00147994) [0.047]	0.00112124 (0.000637823) [0.079]	0.00000937953 (0.0000294015) [0.750]
DIMEMP	0.00955022 (0.00422582) [0.024]	0.010136 (0.00664303) [0.127]	0.000865388 (0.000689594) [0.210]	0.0000538461 (0.000047885) [0.261]		
DTCOCI	0.090836 (0.078908) [0.250]			0.000320437 (0.000357233) [0.370]		
ANTIG	0.426165 (0.309236) [0.168]			0.00385472 (0.00118789) [0.001]		
TRTNIPC	0.198485 (0.148831) [0.182]			0.00327213 (0.0026764) [0.221]		
SSE	2.01961	2.69660		1.66106	3.11624	
R2	0.623884	0.497659		0.695858	0.421689	
Kullback-Leibler R2	0.582801	0.463237		0.683521	0.454013	
Fraction of Correct Predictions	0.900000	0.866667		0.933333	0.80000	
Log Lik.	-6.79959	-8.74826		-5.15804	-8.89859	
Chi-square		3.2346529 [0.51935; 4]			3.4659523 [0.32520; 3]	

Notice that these models explain sector strike occurrence and not individual strike incidence. Industry concentration, intermediate product changes and, to some extent, firm size affect pure sector strike occurrence. Sign effects are consistent with the ones found in the linear models, except, in the enlarged versions, those of employment growth (DTCOCI), which are now positive but insignificant – Newton´s standard errors would make them even more irrelevant.

In the last line of the Table, the encompassing model of versions (17A) and (18A) – which achieved a log-likelihood of – 4,83842 - is tested against each of them (Wald statistic reported). The restrictions were not rejected – rejecting unilaterally both 17A and 18A; yet, the p-values render the rejection of model (18A) as weaker. (The chi-square critical value for a 5% significance test with 3 degrees of freedom is 7,81; with 4 d.f., 9,49 – the likelihood ratio test would barely accept (18A), rejecting the null that the coefficients of weighted (by square root of TCOCI) variables are zero; and would reject (17A), not rejecting that the coefficients of unweighted variables are zero.

3. Using specification (18A), we considered the sample selection of both (weighted) regressions and sought a restricted version of the linear equation of the sample selection models. Results are presented in Table 15:

Table 15

Independent Variables	TGRPT	TGRPT	HGRPT	HGRPT
CONSTANT	-0.087188 (0.062146) [0.161]	-0.125328 (0.068068) [0.066]	-0.885849 (0.583078) [0.129]	-0.568280 (0.426716) [0.183]
IG	-0.103700 (0.173994) [0.551]		-0.607631 (1.39154) [0.662]	
DIMEMP	0.000109922 (0.0000610892) [0.072]	0.0000793627 (0.0000640177) [0.215]	0.00156402 (0.000619681) [0.012]	0.00181694 (0.0011801) [0.124]
TSIND	0.000856914 (0.000868886) [0.324]		0.00463027 (0.00692823) [0.504]	
DTCOCI	-0.00349522 (0.00289324) [0.227]		-0.017520 (0.026334) [0.506]	
ANTIG	0.013240 (0.00965405) [0.170]	0.017444 (0.00564314) [0.002]	0.138040 (0.081733) [0.091]	0.120766 (0.042308) [0.004]
DANTIG	-0.089514 (0.056533) [0.113]	-0.105537 (0.070603) [0.135]		
DIDADE			-0.176201 (0.538112) [0.743]	
TRTNIPC	0.00484336 (0.00375720) [0.197]	0.00334969 (0.00283123) [0.237]	0.031961 (0.031032) [0.303]	
VABT	-0.0000121405 (0.00000557377) [0.029]	-0.0000145978 (0.00000622669) [0.019]	-0.000104903 (0.0000633799) [0.098]	-0.000133801 (0.0000407564) [0.001]
PINTC	0.00300187 (0.00205747) [0.145]	0.00376803 (0.00173645) [0.030]	0.021454 (0.016261) [0.187]	0.020146 (0.00963161) [0.036]
SIGMA	8.56882 (8.89403) [0.335]	10.1862 (4.18556) [0.015]	83.1063 (534.596) [0.876]	81.0244 (23.6151) [0.001]
RHO	0.988171 (62.8318) [0.987]	0.988192 (21.8185) [0.964]	0.999930 (44.986.9) [1.00]	0.643560 (0.914544) [0.482]
Log Likelihood	-84.8955	-88.0719	-136.638	-141.410

RHO does not show significance, not even if we move to shorter versions - its estimate is always positive and very high in regressions over TGRPT. Nevertheless, the sign of the remaining variables stood the change in the model – yet, significance was lost for industry concentration, unionisation and others. Tenure, firm size, labor productivity and the growth rate of other inputs remained significant in all cases.

Positive correlation between the residuals of both sample section equations would produce inconsistent estimates of OLS regression on the non-zero observations, and, possibly, an upward bias of the coefficients inferred from such a regression.

4. Finally, we present the (weighted) TOBIT´s:

Table 16				
Independent Variables	TGRPT	Marginal Effects	HGRPT	Marginal Effects
CONSTANT	-0.095769 (0.035835) [0.008]	-0.0820383 (0.0312140) [0.009]	-0.886247 (0.369996) [0.017]	-0.762553 (0.321104) [0.018]
IG	-0.086736 (0.079389) [0.275]	-0.0743004 (0.0689224) [0.281]	-0.840164 (0.780219) [0.282]	-0.722901 (0.678500) [0.287]
DIMEMP	0.000147369 (0.0000403257) [0.000]	0.000126240 (0.0000352226) [0.000]	0.00199603 (0.000406595) [0.000]	0.00171744 (0.000365355) [0.000]
TSIND	0.000537568 (0.00039054) [0.169]	0.000460497 (0.000340465) [0.176]	0.00388393 (0.00388180) [0.317]	0.00334184 (0.00336719) [0.321]
DTCOCI	-0.00277079 (0.00125423) [0.027]	-0.00237355 (0.00109139) [0.030]	-0.014671 (0.012534) [0.242]	-0.0126235 (0.0108630) [0.245]
ANTIG	0.013043 (0.00500661) [0.009]	0.0111733 (0.00444613) [0.012]	0.143367 (0.048615) [0.003]	0.123358 (0.0432215) [0.004]
DANTIG	-0.100294 (0.026218) [0.000]	-0.0859149 (0.0221290) [0.000]		
DIDADE			-0.074741 (0.101514) [0.462]	-0.06430957 (0.0874719) [0.462]
TRTNIPC	0.00437194 (0.00171321) [0.011]	0.00374514 (0.00152720) [0.014]	0.032408 (0.017221) [0.060]	0.0278847 (0.0151914) [0.066]
VABT	-0.000010791 (0.00000322833) [0.001]	-0.00000924389 (0.00000278116) [0.001]	-0.000111142 (0.0000372292) [0.003]	-0.0000956298 (0.0000319401) [0.003]
PINTC	0.00359068 (0.000914845) [0.000]	0.00307589 (0.000786148) [0.000]	0.023966 (0.00896026) [0.007]	0.0206208 (0.00773376) [0.008]
SIGMA	7.19041 (1.06591) [0.0000]		72.5409 (10.9257) [0.000]	
Log Likelihood	-82.5240		-136.572	
LM test for TOBIT [df]	37.554 [10] *		35.427 [10] *	

* The chi-squared critical value for a 5% significance level for 10 df is 18.3; the TOBIT restrictions of equal coefficients in the censored and uncensored blocks would be rejected.

This regression seems the most appropriate to explain industry strike incidence and severeness, with most coefficients (all but IG and TSIND) significant at the 10% level for the regression on TGRPT.

These TOBIT models are not nested in the sample selection ones – yet, log-likelihoods are higher, even if the global model has a smaller number of parameters than the sample-selection versions presented in Table15.

4.2. Incidence: Cumulative Normal Approaches to (Grouped) Mean Data

Consider an index function interpretation of the binary choice model. Let $TGRPT_{ti}$ denote the variable that represents whether the individual t in sector i engaged in a strike or not, defined in such a way that

$$TGRPT_{ti} = 1 \quad \text{if} \quad \beta' X_{ti} + \varepsilon_{ti} > 0$$
$$TGRPT_{ti} = 0 \quad \text{if} \quad \beta' X_{ti} + \varepsilon_{ti} \leq 0$$

where ε_{ti} has mean zero. Then:

$$Prob(TGRPT_{ti} = 1) = Prob(\beta' X_{ti} + \varepsilon_{ti} > 0) = Prob(\varepsilon_{ti} > - \beta' X_{ti})$$

Being the distribution symmetric, as the normal:

$$Prob(TGRPT_{ti} = 1) = Prob(\varepsilon_{ti} < \beta' X_{ti}) = F(\beta' X_{ti})$$

The variance of ε_{ti} is standardized as 1 and assumed equal across individuals. The model is usually estimated maximizing the log likelihood function:

$$(19) \quad \text{Log L} = \sum_{i=1}^{30} \sum_{t=1}^{n_i} \{TGRPT_{ti} \log F(\beta' X_{ti}) + (1 - TGRPT_{ti}) \log[1 - F(\beta' X_{ti})]\}$$

With symmetry, as in the normal or logistic:

$$(20) \quad \text{Log L} = \sum_{i=1}^{30} \sum_{t=1}^{n_i} [TGRPT_{ti} \log F(\beta' X_{ti}) + (1 - TGRPT_{ti}) \log F(- \beta' X_{ti})]$$

Unfortunately, we only have mean data. We observe

$$\text{TGRPT}_i = \sum_{t=1}^{n_i} \frac{TGRPT_{ti}}{n_i} \quad ; \qquad \text{X}_i = \sum_{t=1}^{n_i} \frac{X_{ti}}{n_i}$$

In the following sections, we developed the research in three different directions: in section A, we propose Probit approximations to mean data. In section B, we apply proportion-based algorithms to the strictly positive observations; we also suggest some fit measures to compare the different structures. Finally, in C, we adapt TOBIT-like structures to the previous modelling to use the null observations.

A. Weighted PROBIT´s

1. We considered three specifications embedding observation fractioning.

$$(21) \qquad \text{Log L} = \sum_{i=1}^{30} n_i\,[\text{TGRPT}_i \log\Phi(\beta' X_i) + (1 - \text{TGRPT}_i) \log\Phi(-\beta' X_i)]$$

Formulation (21) reproduces the maximization of the standard likelihood, (20), if $X_{ti} = X_i$, t=1,2,…n_i. However, that is not the case. And if $F(\beta' X_{ti})$ above is n(0, 1), the cumulative distribution function of its mean, $F(\beta' X_i)$ is indeed normal with mean 0 but with variance n_i^{-1}; then $F(\beta' \sqrt{n_i}\, X_i)$ is the standard normal. A modification of (21) results in:

$$(22) \qquad \text{Log L} = \sum_{i=1}^{30} [\text{TGRPT}_i \log\Phi(\beta' \sqrt{n_i}\, X_i) + (1 - \text{TGRPT}_i) \log\Phi(-\beta' \sqrt{n_i}\, X_i)]$$

(22) implies that the observed distribution of $\beta' X_i$, $F(\beta' X_i)$ has a smaller variance than the individual distribution, the parameters of which we want to estimate.

(22) does not include (double…) weighting by n_i: it assumes a sample of 30 observations and that:

$$\text{Prob}(\text{TGRPT}_i > 0) = \text{Prob}(\beta' \sqrt{n_i}\, X_i + \sqrt{n_i}\ \varepsilon_i > 0) = \Phi(\beta' \sqrt{n_i}\ X_i)$$

being observed a fraction $TGRPT_i$ of the times. For the sake of completeness, we also estimated the model:

$$(23) \qquad \text{Log L} = \sum_{i=1}^{30} n_i \,[TGRPT_i \log\Phi(\beta' \sqrt{n_i}\, X_i) + (1-TGRPT_i)\log\Phi(-\beta' \sqrt{n_i}\, X_i)]$$

For comparability, Log L was divided by the mean of n_i in (21) and (23). However, these specifications turned out to be worse than the unweighted PROBIT if we rely on Newton´s standard-errors. Eicker-White´s algorithm (TSP) originated reasonable t-ratios for models (21) and (23). We present the corresponding results in Table 17.

Table 17			
Independent Variables	(21) E-W	(22) E-W	(23) E-W
CONSTANT	-3.54920 (0.265176) [0.000]	-0.00799601 (0.00709425) [0.260]	-0.00288492 (0.00130617) [0.027]
IG	-0.457415 (0.710054) [0.519]	-0.00397865 (0.015870) [0.802]	0.020758 (0.00430628) [0.000]
DIMEMP	0.000837415 (0.000178528) [0.000]	0.00000770964 (0.00000353984) [0.029]	0.00000341215 (0.00000156748) [0.029]
TSIND	0.00189393 (0.00433956) [0.663]	-0.00000197041 (0.0000723996) [0.978]	-0.0000411429 (0.0000344460) [0.232]
DTCOCI	-0.056470 (0.014517) [0.000]	-0.000000321902 (0.000269766) [0.999]	-0.000236113 (0.000143481) [0.100]
ANTIG	0.108914 (0.032761) [0.001]	0.000255692 (0.00113922) [0.822]	-0.00103738 (0.00026901) [0.000]
DANTIG	-0.768004 (0.230830) [0.001]	-0.00972894 (0.00440054) [0.027]	-0.00556364 (0.00148603) [0.000]
TRTNIPC	0.050180 (0.013154) [0.000]	-0.000135712 (0.000331689) [0.682]	-0.000411905 (0.0000655409) [0.000]
VABT	-0.0000650681 (0.0000283072) [0.022]	-0.000000696243 (0.000000392425) [0.076]	-0.000000660353 (0.000000218513) [0.003]
PINTC	0.040681 (0.012512) [0.001]	0.000180010 (0.00014215) [0.205]	0.000150301 (0.0000574787) [0.009]
Log Likelihood	-3.51125	-6.82280	-3.64366

2.1. Consider an index function interpretation of the a probability model of the form:

$$TGRPT_{ti} = 1 \quad \text{if} \quad F(\beta' X_{ti}) + \varepsilon_{ti} > 0$$
$$TGRPT_{ti} = 0 \quad \text{if} \quad F(\beta' X_{ti}) + \varepsilon_{ti} \leq 0$$

where ε_{ti} has mean zero. Then:

$$\text{Prob}(\text{TGRPT}_{ti} = 1) = \text{Prob}[F(\beta' X_{ti}) + \varepsilon_{ti} > 0] = \text{Prob}[\varepsilon_{ti} > - F(\beta' X_{ti})]$$

Being the distribution of ε_{ti}, with p.d.f. G(.), symmetric, as the normal:

$$\text{Prob}(\text{TGRPT}_{ti} = 1) = \text{Prob}[\varepsilon_{ti} < F(\beta' X_{ti})] = G[F(\beta' X_{ti})]$$

Whatever the variance of ε_{ti}, the variance of its mean will be a fraction n_i – and, by central limit theorem, whatever $G(\varepsilon_{ti})$, the distribution of $\sqrt{n_i}\,\varepsilon_i$ (ε_i is the mean of ε_{ti}) will tend to the normal, with the same mean and variance. Assume $\text{Var}(\varepsilon_{ti})$ is σ^2; also, that F(.) is the standard normal then:

$$\text{Prob}[\sqrt{n_i}\,\varepsilon_i / \sigma < \sqrt{n_i} \sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i} / \sigma] = \Phi[\sqrt{n_i} \sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i} / \sigma]$$

2.2. Unfortunately, we do not observe $\sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i}$. We may consider, yet that it tends to the same pdf evaluated at $\sum_{t=1}^{n_i} \frac{\beta' X_{ti}}{n_i}$ - that would be the case for a linear function F(.). If $F(\beta' X_{ti})$ is the standard normal, then we could replace $F(\beta' X_i) = \Phi(\beta' X_i)$ and admit

$$\text{Prob}(\text{TGRPT}_i = 1) = \Phi[\sqrt{n_i}\, \Phi(\beta' X_i) / \sigma]$$

Similarly:

$$\text{Prob}(\text{TGRPT}_i = 0) = \text{Prob}[\sqrt{n_i}\,\varepsilon_i / \sigma > \sqrt{n_i} \sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i} / \sigma] =$$
$$= 1 - \Phi[\sqrt{n_i}\, \Phi(\sqrt{n_i}\, \beta' X_i) / \sigma] = \Phi[-\sqrt{n_i}\, \Phi(\beta' X_i) / \sigma]$$

$\text{Prob}(\text{TGRPT}_i = 1)$ is observed TGRPT_i percent of the times, and $\text{Prob}(\text{TGRPT}_i = 0)$, $(1 - \text{TGRPT}_i)$ percent. Then, we can write:

(24) $$\text{Log L} = \sum_{i=1}^{30} \{\text{TGRPT}_i \log\Phi[\sqrt{n_i}\,\Phi(\beta' X_i) / \sigma] + (1-\text{TGRPT}_i) \log\Phi[-\sqrt{n_i}\,\Phi(\beta' X_i) / \sigma]\}$$

2.3. However, if F(.) is the standard normal, $\sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i}$ may as well be approximated by $\Phi(\beta' X_i \sqrt{n_i})$, the distribution of the mean of a standard normal variable. In accordance, (24) could be re-written as

(25) $$\text{Log L} = \sum_{i=1}^{30} \{\text{TGRPT}_i \log\Phi[\sqrt{n_i}\,\Phi(\beta' X_i \sqrt{n_i}) / \sigma] + (1-\text{TGRPT}_i) \log\Phi[-\sqrt{n_i}\,\Phi(\beta' X_i \sqrt{n_i}) / \sigma]\}$$

Alternatively, we might reason in the opposite direction: if F(.) is the standard normal, $F(\beta' X_i)$ will present a lower variance than $F(\beta' X_{ti})$, and hence, of any distribution representing $\sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i}$. The observed distribution $F(\beta' X_i)$ has a much smaller variance (n_i times smaller) than the original individual pdf, the parameters of which we want to estimate. Then, the latter may as well be approximated by $\Phi(\beta' X_i / \sqrt{n_i})$ and yield:

(26) $$\text{Log L} = \sum_{i=1}^{30} \{\text{TGRPT}_i \log\Phi[\sqrt{n_i}\,\Phi(\beta' X_i / \sqrt{n_i}) / \sigma] + (1-\text{TGRPT}_i) \log\Phi[-\sqrt{n_i}\,\Phi(\beta' X_i / \sqrt{n_i}) / \sigma]\}$$

2.4. Let us illustrate with a simple numerical example. Consider the sample (2, 3, 7, 8, 10); then; $\sum_{i=1}^{5} \frac{\Phi(Y_i)}{5} = 0.99518$, $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5}) = 1.00000$, $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5} / \sqrt{5}) = 0.99635$, $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5} \sqrt{5}) = 1.00000$. With a sample (0.2, 0.3, 0.7, 0.8, 1.0), $\sum_{i=1}^{5} \frac{\Phi(Y_i)}{5} = 0.71694$, $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5}) = 0.72575$, $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5} / \sqrt{5}) = 0.60578$ and $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5} \sqrt{5}) = 0.91014$.

Now, assume we standardize the values of the sample(s) so that we have a unit variance zero mean sample, then, $\sum_{i=1}^{5} \frac{\Phi(Y_i)}{5}$ = 0.50529 and, obviously, $\Phi(\sum_{i=1}^{5} \frac{Y_i}{5}) = \Phi(\sum_{i=1}^{5} \frac{Y_i}{5} / \sqrt{5}) = \Phi(\sum_{i=1}^{5} \frac{Y_i}{5} \sqrt{5}) = 0.5$.

That is, if observed $F(\beta'X_i)$ is close to 1, or symmetrically, to 0, as in our sample, it would seem that $\Phi(\beta'X_i/\sqrt{n_i})$ becomes closer to $\sum_{t=1}^{n_i} \frac{\Phi(\beta'X_{ti})}{n_i}$ than $\Phi(\beta'X_i)$.

(24), (25) and (26) were also performed but, in general results were very poor.

2.5. Consider a second-order Taylor expansion of $F(\beta' X_{ti})$ around 0:

$$F(\beta' X_{ti}) = F(0) + \beta' X_{ti} f(0) + \frac{(\beta' X_{ti})^2}{2!} f'(0) + \ldots$$

where f(.) denotes the density. If F(.) denotes the cumulative standard normal, then $F(0) = 0.5$, $f(0) = (2\pi)^{-0.5}$ and $f'(0) = 0$. Then the previous expression becomes:

$$\Phi(\beta' X_{ti}) = 0.5 + \beta' X_{ti} (2\pi)^{-0.5} + \ldots$$

That is, a second-order approximation to the cumulative normal yields a linear probability function – suggesting that, apart from the constant term, marginal effects will scale down the coefficients of a probit model by $(2\pi)^{-0.5}$, i.e., 0.398942 ($\phi(\beta' X_{ti})$, the standard normal density, evaluated at 0) [83], the expected relation with the linear probability model coefficients. Then:

$$\sum_{t=1}^{n_i} \frac{\Phi(\beta'X_{ti})}{n_i} = 0.5 + \beta'X_i (2\pi)^{-0.5} + \ldots$$

---

[83] For the logistic, with $F(\beta' X_{ti}) = \frac{e^{\beta' x_{ti}}}{1+e^{\beta' x_{ti}}}$, $F(0) = 0.5$, $f(0) = F(0)[1-F(0)] = 0.25$ $f'(0) = 0$. Then the expression becomes: $F(\beta' X_{ti}) = 0.5 + 0.25 \beta' X_{ti} + \ldots$. Of course, we expect that $0.25 \beta_{Logistic} = (2\pi)^{-0.5} \beta_{Probit}$, that is, $\beta_{Probit} = 0.25 (2\pi)^{0.5} \beta_{Logistic} = 0.626657 \beta_{Logistic}$, or $\beta_{Logistic} = 1.595769 \beta_{Probit}$.

which approximates (to the second-order) the expansion of $\Phi(\beta' X_i)$ around 0. Of course, this approximation – the Taylor expansion – works best for small $\beta' X_i$, implying observed frequencies around 0.5, which is not the case for strike incidence in our sample.

B. Minimum Chi-square Estimators of Cumulative Normals.

B.1. Proportions Data and Cumulative Normals

1. As sometimes referred in the literature, for the positive observations of TGRPT, we advance that:

$$(27) \qquad F^{-1}(TGRPT_i) = \beta' X_i + \eta_i \quad , \quad TGRPT_i > 0$$

Then, $\eta_i = \dfrac{\varepsilon_i}{f_i}$; under the Bernoulli environment, $Var(\eta_i) = [\dfrac{n_i f_i^2}{F_i(1-F_i)}]^{-1}$ where f_i is the density and F_i cumulative distribution at $\beta' X_i$. Assuming the standard normal, a two-step weighted least squares yielded the required improved estimate [84], with $f_i = \phi(\hat{\beta}' X_i)$ and $F_i = \Phi(\hat{\beta}' X_i)$.

2.1. Being X_i means, and under the above reasoning, F(.) may not stand for a uniform variance normal. We may assume that $F(\beta' X_i)$ has a normal distribution with mean zero (a non-zero mean, constant across observations, is captured in the intercept) and variance n_i^{-1}; then $F^{-1}(TGRPT_i)$ will equal $\Phi^{-1}(TGRPT_i)$ multiplied by the standard deviation of the distribution F(.). Therefore, we reformulated (27) considering:

$$(28) \qquad F^{-1}(TGRPT_i) = \Phi^{-1}(TGRPT_i) / \sqrt{n_i} = \beta' X_i + \eta_i$$

$Var(\eta_i) = [\dfrac{n_i f_i^2}{F_i(1-F_i)}]^{-1}$. This was approximated from the first OLS regression replacing $f_i = \phi(\hat{\beta}' \sqrt{n_i} X_i)$ and $F_i = \Phi(\hat{\beta}' \sqrt{n_i} X_i)$; the second WLS step was performed correcting for such heteroscedasticity – a minimum chi-square estimation approach.

[84] See Greene (2000), p. 834-837, for example.

2.2. (28) can be re-written as

(29) $$\Phi^{-1}(TGRPT_i) = \beta' \sqrt{n_i}\, X_i + \sqrt{n_i}\, \eta_i = \beta' \sqrt{n_i}\, X_i + \nu_i$$

with $Var(\nu_i) = [\frac{f_i^2}{F_i(1-F_i)}]^{-1}$. This model is equivalent to the previous one, and the first step approximation of heteroscedasticity correction allows the estimation of $f_i = \phi(\hat{\beta}' \sqrt{n_i}\, X_i)$ and $F_i = \Phi(\hat{\beta}' \sqrt{n_i}\, X_i)$.

(29) could be inducted from an index function interpretation as above with $F(\beta' X_{ti}) = \beta' X_{ti}$. Then $\sum_{t=1}^{n_i} \frac{F(\beta' X_{ti})}{n_i} = \beta' X_i$ and

$$TGRPT_i = Prob(TGRPT_{ti} = 1) + \varepsilon_i = G(\beta' X_i / \sigma) + \varepsilon_i$$

σ is undetermined, hence fixed to 1 and G(.) is the normal distribution with mean zero and variance n_i^{-1}. We observe 30 observations.

3. Finally, we could argue that $F(\beta' X_i)$ exhibits a smaller variance than the distribution we want to capture, the mean distribution of $\Phi(\beta' X_{ti})$. Then:

(30) $$F^{-1}(TGRPT_i) = \Phi^{-1}(TGRPT_i) \sqrt{n_i} = \beta' X_i + \eta_i$$

$Var(\eta_i) = [\frac{n_i f_i^2}{F_i(1-F_i)}]^{-1}$ that can approximated from the first OLS regression replacing $f_i = \phi(\hat{\beta}' X_i / \sqrt{n_i})$ and $F_i = \Phi(\hat{\beta}' X_i / \sqrt{n_i})$.

B.2. Comparison of Formulations

The four formulations were estimated. We summarize in Table 18 below the implicit sum of squared distances of the inverse standard cumulative normal predictions of models (27), (28) and (30) from $\Phi^{-1}(TGRPT_i)$, SSFI, and the sum of the corresponding absolute distances, ABSFI [85]. They can (distantly) be related to Zavoina and McElvey´s (1975) measure of goodness of fit.

Nevertheless, what we are trying to explain is TGRPT; hence, the sum of square distances of the predicted frequencies from $TGRPT_i$:

$$SST = \sum_{i=1}^{30} (TGRPT_i - \hat{TGRPT}_i)^2$$

and the sum of absolute distances:

$$ABST = \sum_{i=1}^{30} |TGRPT_i - \hat{TGRPT}_i|$$

are also reported. $\hat{TGRPT}_i$ are computed from the appropriate cumulative normal pdf evaluated at $\hat{\beta}'X_i$. Legitimately, we could as well have searched for the minimum weighted sum of squares by n_i or n_i^2,

$$SST1 = \sum_{i=1}^{30} n_i (TGRPT_i - \hat{TGRPT}_i)^2$$

$$SST2 = \sum_{i=1}^{30} n_i^2 (TGRPT_i - \hat{TGRPT}_i)^2 = \sum_{i=1}^{30} [n_i (TGRPT_i - \hat{TGRPT}_i)]^2$$

and weighted sums of absolute deviations by $\sqrt{n_i}$ or n_i.

$$ABST1 = \sum_{i=1}^{30} \sqrt{n_i}\, |TGRPT_i - \hat{TGRPT}_i|$$

$$ABST2 = \sum_{i=1}^{30} n_i |TGRPT_i - \hat{TGRPT}_i| = \sum_{i=1}^{30} |n_i (TGRPT_i - \hat{TGRPT}_i)|$$

SST1 is comparable with the sum of squares minimized by weighted least squares (above) when the weight is n_i – or of the transformed linear model through multiplication by $\sqrt{n_i}$ of both the left and right hand-side (provided all observations are being used).

[85] See Greene, p. 832.

The criteria based on SST2 and ABST2 would imply a minimization of the sum of the distances of total effective or observed from total predicted strikers in the each industry; for instance, SST2 is comparable to the sum of squared residuals of a regression where the dependent variable is the aggregate number of occurrences (if all observations are used, like the regression in Appendix 3 on NT94T, Table C.1).

Another possibility would search for the model that yields the smaller value of the aggregate prediction error (however, this would be a second rate criteria once positive and negative industry prediction errors, being large, could cancel out and yield a low ABST3):

$$ABST3 = \left| \sum_{i=1}^{30} n_i \left(TGRPT_i - \widehat{TGRPT}_i\right) \right|$$

The analogous indicators for the inverse standard normal predictions are also reported:

$$SSFI1 = \sum_{i=1}^{30} n_i \left[\Phi^{-1}(TGRPT_i) - \Phi^{-1}(\widehat{TGRPT}_i)\right]^2$$

$$SSFI2 = \sum_{i=1}^{30} n_i^2 \left[\Phi^{-1}(TGRPT_i) - \Phi^{-1}(\widehat{TGRPT}_i)\right]^2$$

$$ABSFI1 = \sum_{i=1}^{30} \sqrt{n_i} \left|\Phi^{-1}(TGRPT_i) - \Phi^{-1}(\widehat{TGRPT}_i)\right|$$

$$ABSFI2 = \sum_{i=1}^{30} n_i \left|\Phi^{-1}(TGRPT_i) - \Phi^{-1}(\widehat{TGRPT}_i)\right|$$

(We are choosing among different functional forms with the same number of parameters, or different non-linear estimators. If the literature proposes some tests to compare specific formulations they are not always applicable in our case; moreover, data are frequencies and the usual predictions used for individual binary data are not adequate. SST´s and ABST´s presented above have universal meaning, predictions of the dependent variable can always be calculated from cumulative cdf´s, and should not be neglected.

Given the range of the normal density, going from minus to plus infinity as the cumulative distribution function goes from 0 to 1, the measures based on inverse probabilities can only be computed for proportion data. Alternatively, for the observations for which $TGRPT_i$ is zero, $\Phi^{-1}(TGRPT_i)$ can be replaced by $\Phi^{-1}(0.5 / TCOCI_i)$, where TCOCI is the total number of individuals in sector i – not even one individual in the sector was involved in strikes; if some $TGRPT_i$ were equal to 1, we would replace, consistently, $\Phi^{-1}(TGRPT_i)$ by $- \Phi^{-1}(0.5 / TCOCI_i) = \Phi^{-1}[(TCOCI_i - 0.5) / TCOCI_i]$.)

Table 18

		Equation		
SUMS	LS	(27)	(28)	(30)
SSFI	OLS	5.75537 #	14.85140	57.30885
	WLS	9.37697	92.19982	218.32038
SSFI1	OLS	297290.15649	1396983.25592	1035480.70916
	WLS	190490.88291 #	1.30896D+7	1918922.8234
SSFI2	OLS	2.9155D+10	1.97706D+11	9.26020D+10
	WLS	1.57116D+10 #	2.10834D+12	8.17935D+10
ABSFI	OLS	9.19302	12.34306	23.22928
	WLS	7.99471 #	24.59548	36.01429
ABSFI1	OLS	1972.09868	3280.57294	3832.95642
	WLS	1406.49805 #	7665.26242	4913.20849
ABSFI2	OLS	537809.61072	1049137.13407	948367.46313
	WLS	353190.92499 #	2653619.70210	1019198.94702

Table 18 (Cont.)

SUMS	LS	Equation (27)	(28)	(30)
SST	OLS	0.052362	0.078664	0.19682
	WLS	0.040501	0.018383 #	0.091041
SST1	OLS	1023.46926	3088.55297	3506.65985
	WLS	547.72146 #	726.62061	1408.37272
SST2	OLS	4.59292D+7	2.80743D+8	1.57829D+8
	WLS	2.04845D+7 #	5.64248D+7	4.42994D+7
ABST	OLS	0.65379	0.77977	1.22520
	WLS	0.45599	0.41654 #	0.79499
ABST1	OLS	103.88317	155.29480	194.03454
	WLS	62.75410 #	75.78531	114.87022
ABST2	OLS	22220.76881	40458.49157	41636.73112
	WLS	12276.09791 #	18490.17036	22103.40315
ABST3	OLS	5999.26354	(-)3782.87036 #	(-)15081.20048
	WLS	5975.79902	8280.46649	7969.35615

After correcting for heteroscedasticity, predictions of TGRPT from (28) yielded a smaller value of both SST and ABST. WLS on (27) gave better results for all other measures except ABST3 – interestingly, the overall aggregate deviation is smaller for the formulation based on (29) – results of which were not presented once equivalent and worse than (28) -, followed by (28).

(27) to (30) can only be estimated for non-zero observations of TGRPT; hence, we loose information on the other sectors, which is, after all, available. Therefore, a two-step TOBIT type estimator is advanced below:

C. Weighted TOBIT Models

1.1. We admit for $TGRPT_i > 0$, which is observed a process based on (27). Then:

$$\text{(31)} \quad -\Phi^{-1}(TGRPT_i)\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\sqrt{n_i} =$$

$$= \Phi^{-1}(1-TGRPT_i)\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}} = -\beta'\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}X_i + \nu_i$$

$\sqrt{\frac{f_i^2}{F_i(1-F_i)}}$ was computed, as previously, from predictions of a first OLS regression on (27).

(Note that in our sample $\Phi^{-1}(TGRPT_i) \leq 0$ always; the sign of observations involved in the previous equation are, therefore, reversed.).

For $TGRPT_i = 0$, $\quad Prob(TGRPT_i = 0) = Prob(\beta'\sqrt{n_i}X_i + \nu_i \leq 0) = F(-\beta'\sqrt{n_i}X_i)$.

Therefore, leaving the variance, σ_ν^2, of the distribution free and assuming a mean zero normal, we maximize:

$$\text{(32)} \quad \text{Log L} = \sum_{i=1}^{30} [(1-TGRPT1_i)\log\Phi(-\beta'\sqrt{n_i}X_i / \sigma_\nu) +$$

$$+ TGRPT1_i \log\phi\{[\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\Phi^{-1}(1-TGRPT_i) + \beta'\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}X_i)] / \sigma_\nu\}$$

where $\phi(.)$ denotes the standard normal density function. With a re-parameterisation of variables, we could use the TOBIT algorithm to estimate β.

(We might have as well admitted $\Phi(-\beta'X_i / \sigma_\nu)$ in the likelihood function. We consider we are weighting the error term when averaging – see appendix 4.)

1.2. Correcting consistently the variance of the non-zero observations, following (28) or (29),

$$\text{(33)} \quad \Phi^{-1}(TGRPT_i) = \beta'\sqrt{n_i}X_i + \sqrt{n_i}\eta_i =$$

$$= \beta'\sqrt{n_i}X_i + \nu_i$$

with $Var(\nu_i) = [\frac{f_i^2}{F_i(1-F_i)}]^{-1}$, calculated according to form (28) – given the better fit of (28) relative to (29), we used them for the correction of heteroscedasticity and specified:

For $TGRPT_i = 0$, $Prob(TGRPT_i = 0) = Prob(\beta' \sqrt{n_i} X_i + \nu_i \leq 0) = F(-\beta' \sqrt{n_i} X_i)$, but F(.) has variance n_i^{-1}.

$$(34) \quad \text{Log L} = \sum_{i=1}^{30} [(1-TGRPT1_i) \log\Phi(-\beta' n_i X_i / \sigma_\nu) +$$

$$+ TGRPT1_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}} \Phi^{-1}(1-TGRPT_i) + \beta' \sqrt{n_i} \sqrt{\frac{f_i^2}{F_i(1-F_i)}} X_i)] / \sigma_\nu\}$$

(Note that (28) or (29) generate this same model.)

1.3. Finally, consistent with (30):

$$(35) \quad \text{Log L} = \sum_{i=1}^{30} [(1-TGRPT1_i) \log\Phi(-\beta' X_i / \sigma_\nu) +$$

$$+ TGRPT1_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}} n_i \Phi^{-1}(1-TGRPT_i) + \beta' \sqrt{n_i} \sqrt{\frac{f_i^2}{F_i(1-F_i)}} X_i)] / \sigma_\nu\}$$

1.4. Note that the use of the TOBIT algorithm is dictated by its computational convenience, once it is included in most computer packages, converging quickly. Maximum likelihood estimation could offer other alternatives, including the non-inversion of the pdf of the non-zero observations – and correspondingly multiplying both sides by $\sqrt{\frac{n_i}{F_i(1-F_i)}}$ an estimator of the variance of the "original" errors ε_i [86]. That is, (32), for example, could become:

$$\text{Log L} = \sum_{i=1}^{30} [(1-TGRPT1_i) \log\Phi(-\beta' \sqrt{n_i} X_i / \sigma_\nu) +$$

[86] See Greene (2000), p. 835.

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta'X_i)] / \sigma_v\}$$

(σ_v should eventually be fixed to 1.) Estimates of these versions are presented in Appendix 5.

The non-zero observations part of this last model embeds a "double normality" and, in this form, suggests a modification of the other part of the likelihood function – for the no-strike case -, already considered in (24)-(26):

2.1. (28) or (29) are specified for any n_i. They should also be valid for $n_i = 1$, for which we would observe:

$$\text{(36)} \qquad \text{TGRPT}_{ti} = F(\beta'X_{ti}) + \varepsilon_{ti}$$

F(.) stands for the standard normal and $F(\beta'X_{ti})$ approximates the parameter of the binomial distribution for individual t in sector i. (36) is not the linear probability model for which the index function interpretation was forwarded: rather, it could fall into a model of type (24) – then (27) would be the corresponding mean data model –, (25) – generating (30) - or (26) – generating (28) or (29). Then, with the zero observations, (27) yields:

$$\text{(37)} \quad \text{Log L} = \sum_{i=1}^{30} \{(1-\text{TGRPT1}_i) \log\Phi[-\sqrt{n_i}\ \Phi(\beta'X_i) / \sigma_v] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1-\text{TGRPT}_i) + \beta'\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}X_i)] \}$$

(37) would entail TOBIT-like interpretation of the model $Y_i = \Phi(\beta'X_i) + \varepsilon_i$, being TGRPT_i observed (and equal to) only for positive Y_i, and where ε_i has variance n_i^{-1} for the censored observations.

With the second distribution function, F() is the null mean normal but with variance n_i^{-1}, i.e., (28), we would have:

$$\text{(38)} \quad \text{Log L} = \sum_{i=1}^{30} \{(1-\text{TGRPT1}_i) \log\Phi[-\sqrt{n_i}\ \Phi(\beta'X_i\sqrt{n_i}) / \sigma_v] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\ \sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)]\ \}$$

Finally, with the third normal cdf:

$$(39)\quad \text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\Phi[-\sqrt{n_i}\ \Phi(\beta' X_i/\sqrt{n_i}\,) / \sigma_\nu] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ n_i\, \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\ \sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)]\ \}$$

(σ_ν was fixed to 1.)

2.2. If we assume (36), we can as well estimate, from the results (27) and (28) in each case, F_i and f_i for the zero observations. A final specification considered a modification of (37) to (39) accordingly:

$$(40)\quad \text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\phi[-\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i)\ ] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{n_i}\ \sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\ \sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)]\ \}$$

$$(41)\quad \text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\phi[-\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i\sqrt{n_i}\,)] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\ \sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)]\ \}$$

$$(42)\quad \text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\phi[-\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i/\sqrt{n_i}\,)] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ n_i\, \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\ \sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)]\ \}$$

Of course, (again) the non-zero observations of the likelihoods did not have to rely on the inverse pdf´s; but that would introduce additional non-linearity in the estimation.

3. The measures used above were computed for the several models. We report such summary statistics below (for regression (42), $[\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}]^{-1}$ was replaced by a small number and $\sqrt{\frac{n_i}{F_i(1-F_i)}}$ by a large number for three observations, for which approximations of F_i turned out to be close to 0.)

Predictions for zero observations were calculated in two different modes for versions (32)-(39): as for the non-zero ones. And (results in parenthesis) as implied by the cumulative normal of the likelihood function – for instance, for zero observations of version (32), $\hat{TGRPT}_i = \Phi(\hat{\beta}' \sqrt{n_i}\, X_i / \hat{\sigma}_\nu)$ [87]. The measures on inverse probabilities aggregating only the 23 non-zero observations are reported in square brackets.

The smallest value for each criteria of the first mode of predictions is signalled with a #; when the second mode of predictions originated a smaller value, the best was signalled with two ##; for measures on the 23 observations only, the best prediction was signalled with ###. The uniform prediction method yielded best results of inverse normal predictions for models (37) or (40); model (40) originated the best frequency predictions. Non-uniform predictions based on frequencies consistently point to model (32).

Looking only at the first two tables, the approximation $F(\beta' X_i) = \Phi(\beta' X_i)$ – (32) and (37) – are usually better, specially if we consider weighted criteria. $\Phi(\beta' X_i/\sqrt{n_i})$ seems worst in any table for most criteria except SST and ABS, and some non-uniform prediction criteria, for which they seem the best.

Finally, SST1 for versions (32), (37) and (40) yielded lower values than SSE of weighted regressions on TGRPT (Table 12); and SST2 lower than SSE of aggregate version on NT94T (Table C.1 in Appendix 3) – even when the latter has one extra parameter.

[87] See in Appendix 4 the presentation of the likelihood formulations with homogeneous predictions across the two sub-samples. Yet, the forms presented in the main text were theoretically justified above.

Table 19

SUMS	Equation		
	(32)	(34)	(35)
SSFI	30.36190 (539.07517) [9.19196 ###]	70.65659 (5204726.74908) [13.67571]	4007.75394 (311.62812) [221.96398]
SSFI1	756226.31068 (2.12151D+7) [188710.10063 ###]	1505463.79656 (3.2801D+11) [892246.65521]	6009690.63362 (3834862.63679) [1925257.65486]
SSFI2	4.87941D+10 (1.08645D+12) [1.55867D+10 ###]	1.542D+11 (2.11806D+16) [1.32947D+11]	1.17209D+11 (1.77946D+11) [8.17734D+10]
ABSFI	18.85408 (52.53448) [8.02469 ###]	32.70774 (3091.82704) [13.16066]	160.24708 (60.97364) [36.14058]
ABSFI1	2652.01401 (8842.05646) [1419.68312]	4954.32555 (684641.2704) [3330.16528]	9593.59751 (7499.84907) [4915.53378]
ABSFI2	596833.07797 (1851367.83005) [357196.56042]	1310781.15558 (1.63437D+8) [1066935.84564]	1363614.81641 (1477229.91418) [1018497.68750]
SST	0.10610 (0.064194 ##)	0.85772 (0.12294)	0.090677 (1.64678)
SST1	794.13193 (583.51337 ##)	4881.76032 (2814.30381)	1467.81929 (26760.30683)
SST2	3.15526D+7 (2.08494D+7 ##)	2.53861D+8 (2.14574D+8)	4.90325D+7 (1.28718D+9)
ABST	0.83697 (0.66967 ##)	2.95430 (1.07928)	0.82484 (4.09140)
ABST1	87.98083 (70.38824 ##)	273.94245 (177.53869)	123.07435 (424.71474)
ABST2	16241.10531 (12676.76706 ##)	51485.66640 (42139.54054)	24249.82186 (74956.93044)
ABST3	2429.87979 (5994.21804)	1874.01080 # (11220.13666)	5776.11289 ((-)44930.99569)

Table 19 (Cont.)

SUMS	Equation (37)	(38)	(39)
SSFI	30.52192 (493.13932) [9.38295]	520.17575 (578.60544) [446.18466]	3977.79804 (472.63178) 218.32034]
SSFI1	733034.62360 (1.68342D+7) [189509.8407]	6.29476D+7 (6.08779D+7) [5.88503D+7]	5989669.51852 (1.44186D+7) [1918922.7004]
SSFI2	4.73046D+10 (1.05315D+12) [1.56660D+10]	1.17172D+13 (1.15528D+13) [1.14541D+13]	1.17516D+11 (8.6979D+11) [8.17935D+10]
ABSFI	18.81288 (56.65648) [8.03640]	91.94571 (105.68371) [75.37215]	159.59750 (70.43289) [36.01429]
ABSFI1	2632.81112 # (7412.66618) [1418.78501 ###]	25013.43805 (25199.52470) [22403.89581]	9575.11835 (9861.57957) [4913.20852]
ABSFI2	591225.34088 # (1584964.823) [356290.63342 ###]	8585845.21558 (8474428.83008) [8001222.06152]	1363864.03687 (2078222.99048) [1019198.94409]
SST	0.11677 (4.53880)	5.58943 (9.36071)	0.092302 (2.59132)
SST1	749.19124 (91918.92358)	453136.89206 (484569.89585)	1490.91063 (78125.12899)
SST2	2.83390D+7 (4.96278D+9)	5.54965D+10 (5.68602D+10)	4.97000D+7 (4.59211D+9)
ABST	0.84255 (5.89470)	7.36637 (12.18735)	0.83052 (4.79527)
ABST1	85.47761 (609.27512)	1809.04160 (2185.99647)	123.95590 (569.17056)
ABST2	15575.64191 (111412.72559)	542820.33101 (600982.76865)	24427.44139 (110095.41039)
ABST3	2820.59646 # ((-)93016.48722)	(-)467291.37366 ((-)525453.81130)	5645.31205 ((-)80022.65719)

	Table 19 (Cont.)		
	Equation		
SUMS	(40)	(41)	(42)
SSFI	26.33806 # [9.37592]	724.34790 [626.37525]	3977.80083 [218.32195]
SSFI1	643515.114 # [194755.79765]	8.71540D+7 [8.14785D+7]	5989665.91447 [1918924.08366]
SSFI2	4.23352D+10 # [1.68158D+10]	1.59221D+13 [1.55612D+13]	1.17515D+11 [8.17935D+10]
ABSFI	17.953 # [8.39223]	106.77493 [89.02691]	159.59762 [36.01434]
ABSFI1	2668.63981 [1554.30146]	29494.44522 [26411.37285]	9575.11609 [4913.20677]
ABSFI2	625348.99332 [409662.57492]	1.0086D+7 [9385577.11084]	1363862.24585 [1019197.94897]
SST	0.065376 #	6.09549	0.092303
SST1	588.22112 #	492120.75938	1490.91250
SST2	2.32711D+7 #	5.95634D+10	4.96997D+7
ABST	0.67852 #	7.92628	0.83051
ABST1	76.91502 #	1976.70801	123.95562
ABST2	15203.48154 #	592970.65023	24427.35789
ABST3	5237.1177	-515583.68146	5645.41685

We essayed also combing (32) and (21). For instance:

$$\text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i)\, n_i \log\Phi(-\beta' X_i / \sigma_\nu)] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta' \sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ X_i)] /\sigma_\nu\}$$

With σ_v fixed to 1, the criteria for inverse predictions were lower in this model than in (32): SSFI of 26.99651; SSFI1 of 574557.10031; SSFI2 of 3.77179D+10; ABSFI of 17.78964; ABSFI1 of 2604.70881; ABSFI2 of 606311.4413. It generated an SST of 0.085614; SST1 of 555.09049; SST2 of 2.05282D+7; ABST of 0.71139; ABST1 of 74.88136; ABST2 of 14334.38838; which, if larger than the corresponding values for model (32), are smaller than the measures computed with a non-uniform criteria.

We present below the results of equations (32) and (37) – for model (37), Eicker-White standard-errors are presented, once other standard errors (Newton or Berndt et al) were extremely high.

Table 20				
Independent Variables	(32)	Unconditional Marginal Effects	(37) E-W	Unconditional Marginal Effects
CONSTANT	-3.48138 (0.322754) [0.000]	-0.14962 (0.027621) [0.000]	-3.47417 (0.268332) [0.000]	-0.14762 (0.028274) [0.000]
IG	0.761580 (0.787732) [0.334]	0.032731 (0.033250) [0.325]	0.782353 (0.596628) [0.190]	0.033244 (0.022503) [0.140]
DIMEMP	0.000534938 (0.000290304) [0.065]	0.000022991 (0.000012021) [0.056]	0.000569669 (0.000222337) [0.010]	0.000024206 (0.0000089244) [0.007]
TSIND	0.00724951 (0.00490407) [0.139]	0.00031157 (0.00023298) [0.181]	0.00666197 (0.00344126) [0.053]	0.00028308 (0.00014818) [0.056]
DTCOCI	-0.056373 (0.014867) [0.000]	-0.0024228 (0.00079596) [0.002]	-0.058496 (0.013098) [0.000]	-0.0024856 (0.00070143) [0.000]
ANTIG	0.039970 (0.046138) [0.386]	0.0017178 (0.0020111) [0.393]	0.037439 (0.025616) [0.144]	0.0015909 (0.0013028) [0.222]
DANTIG	-0.766329 (0.242636) [0.002]	-0.032935 (0.0083433) [0.000]	-0.778329 (0.173714) [0.000]	-0.033073 (0.0069388) [0.000]
TRTNIPC	0.028922 (0.016799) [0.085]	0.0012430 (0.00078164) [0.112]	0.029478 (0.011057) [0.008]	0.0012526 (0.00060397) [0.038]
VABT	-0.0000497646 (0.0000289948) [0.086]	-0.0000021388 (0.00000116154) [0.066]	-0.0000515270 (0.0000261480) [0.049]	-0.00000218948 (0.000000938520) [0.020]
PINTC	0.024230 (0.012527) [0.053]	0.0010414 (0.00051847) [0.045]	0.026046 (0.013671) [0.057]	0.0011067 (0.00060898) [0.069]
SIGMA	23.0137 (3.33853) [0.000]			
Log Likelihood	-105.256		-6369.6	

Except for industry concentration (IG), the sign effects of the variables remained. IG is no longer significant at the 10% level, neither tenure, ANTIG.

Reported marginal effects measure how an (unitary) increase in the corresponding variable affects the (unconditional latent) probability of (individual) strike occurrence. Standard-errors were calculated using the standard normal derivation [88] – p-values assume standard normality of implied “t-ratios”. Marginal effects are comparable to the estimates of weighted least squares (column TGRPT of Table 12); in general, the absolute value of the coefficients is now smaller – IG is non-significant and, as noticed, its coefficient has switched sign.

4. For the sake of completeness, we re-estimated the last two models including the residuals from the earnings regressions and the time variables. Summary results are reported below on Table 21. The (negative, as hypothesized) significance of the individual inclusion of residuals improved relative to the analogous procedure reported in Table 9; the wage share effects are no longer statistically important. (Eicker – White´s standard-errors, reported, originated similar significances as TOBITS´s TSP algorithm – Newton´s. Berndt *et al* and Newton´s were for versions (37) abnormally high.)

[88] See Greene (2000), p. 824, for example.

Table 21

Independent Variables	(32)	LOGL	(37) E-W	LOGL
REMVA	0.000077866 (0.000120612) [0.519]	-105.538	0.0000701583 (0.0000985774) [0.477]	-6556.6
DREMVA	-0.000604931 (0.000776554) [0.436]	-105.342	-0.000560447 (0.000606776) [0.356]	-6447.68
RES1	-0.0000158920 (0.0000110847) [0.152]	-104.291	-0.0000162821 (0.0000106347) [0.126]	-5853.75
RESL	-0.0000183313 (0.0000122595) [0.135]	-104.543	-0.000019217 (0.0000131766) [0.145]	-5955.12
RES2	-0.00629277 (0.034491) [0.855]	-106.621	-0.00857033 (0.047426) [0.857]	-7148.87
DRES = RES1 - RESL	-0.00000471956 (0.0000291116) [0.871]	-105.221	-0.00000544684 (0.0000205469) [0.791]	-6359.55
RES1	-0.00000204594 (0.0000278784) [0.941]	-104.517	-0.00000210856 (0.0000223012) [0.925]	-5958.9
RESL	-0.0000144071 (0.0000310717) [0.643]		-0.0000151171 (0.0000305743) [0.621]	
RES1	-0.00000669811 (0.0000403955) [0.868]	-105.863	-0.00000498226 (0.0000346519) [0.886]	-6703.11
RESL	-0.00000490210 (0.000043144) [0.910]		-0.00000703179 (0.0000322099) [0.827]	
RES2	-0.00186408 (0.046336) [0.968]		-0.00589475 (0.070837) [0.934]	

Table 21 (Cont.)				
Independent Variables	(32)	LOGL	(37)	LOGL
HCI	0.064724 (0.047468) [0.173]	-104.731	0.064942 (0.046891) [0.166]	-6097.81
HCIVAR	0.019529 (0.00590411) [0.001]	-101.874		
HCISIG	0.312796 (0.091229) [0.001]	-100.940	0.310438 (0.069124) [0.000]	-4428.37
HCICV	9.29869 (2.93809) [0.002]	-102.905	9.63800 (2.52097) [0.000]	-5186.81
HC	0.065065 (0.047655) [0.172]	-104.212	0.065435 (0.044425) [0.141]	-5833.29
HCVAR	0.024727 (0.014647) [0.091]	-104.478	0.026171 (0.010466) [0.012]	-5921.91
HCSIG	0.160262 (0.106713) [0.133]	-104.732	0.167932 (0.082271) [0.041]	-6070.97
HCCV	6.32790 (4.05909) [0.119]	-104.828	6.63175 (3.08899) [0.032]	-6123.87
HNTCOCI	0.059664 (0.050999) [0.242]	-105.305	0.059648 (0.048235) [0.216]	-6395.76
HNTCOC	0.058911 (0.050973) [0.248]	-104.848	0.058946 (0.042693) [0.167]	-6146.41
HTTCOCI	0.035960 (0.039680) [0.365]	-105.321	0.036458 (0.033703) [0.279]	-6393.26

The higher the variability of weekly hours in the sector, the more frequent are strikes. Recall that our theoretical section suggested that a separating equilibrium would be possible with the occurrence of strikes, provided individuals had different preferences over the leisure/work-income baskets; additionally, fixed standard hours equal to everybody (less variability) would decrease strike length needed. Both would suggest a positive coefficient for HCISIG – standard deviation of weekly hours in the sector -, which was found significant at 10% significance level in both regressions.

Weekly hours variability could be related to worker heterogeneity. Diversity in individuals´ preferences and interests would difficult unionisation and we could have reasonably encounter the opposite – negative – effect [89]. The positive value found gives, thus, some support to the theoretical models previously advanced.

[89] On the other hand, weekly hours variability could work through unionisation, which is already controlled for – absence of any effect would also be accounted for.

Table 21 (Cont.)				
Independent Variables	(32)	LOGL	(37)	LOGL
HNAOT93	0.075381 (0.048002) [0.116]	-104.101	0.075541 (0.046779) [0.106]	-5758.03
ANAAT93	0.128431 (0.362492) [0.723]	-104.747	0.144346 (0.290068) [0.619]	-6076.14
ANADN93	0.087327 (0.073892) [0.237]	-104.954	0.089464 (0.073787) [0.225]	-6174.35
ANADP93	1.30560 (2.81901) [0.643]	-105.393	1.15043 (2.10870) [0.585]	-6443.37
ANASD93	-0.675256 (2.96449) [0.820]	-105.190	-0.465311 (2.03087) [0.819]	-6347.42
ANAMP93	0.307953 (0.334481) [0.357]	-104.736	0.299232 (0.269890) [0.268]	-6111.26
ANAOC93	0.082984 (0.107942) [0.442]	-105.063	0.084194 (0.074438) [0.258]	-6246.82
HEXTPC	-0.00546943 (0.046783) [0.907]	-105.178	0.00112423 (0.025856) [0.965]	-6329.43
HEXTPTR	-0.012674 (0.111801) [0.910]	-105.161	0.00273803 (0.062223) [0.965]	-6320.20
TXDES	0.070950 (0.043651) [0.104]	-104.088	0.072628 (0.033852) [0.032]	-5757.81

Most absenteeism coefficients are unimportant, even if HNAOT93 is almost significantly positive at the 10% level.

We also include the unemployment rate – a positive coefficient was found, consistent with the view that strike occurrence decreases in peaks and increases in troughs.

5. Severeness: A Self-selection Weighted Model

We depart from a regression on mean hours of strike in the sector, $HGRPT_i$, described by

(43) $$\sqrt{n_i}\, HGRPT_i = \gamma' \sqrt{n_i}\, Z_i + \mu_i$$

where $Var(\mu_i)$ is assumed constant – that is the original residuals where heteroscedastic with variance proportional to n_i. This equation was suggested by the linear models presented in sector 2 and weighting partly justified by the appendix regressions. However, some observations of the dependent variable are 0. A first approach – suggested in section 2 – included the estimation of sample selection models – and TOBIT´s. Given that we have estimated previous versions of strike incidence models, we can reformulate the standard sample selection procedures to account for the additional information contained in them.

In general, $HGRPT_i$ is observed only if

$$Prob(TGRPT_i > 0) = Prob(\sqrt{n_i}\, F(\beta' X_i) + \sqrt{n_i}\ \varepsilon_i > 0) = \Phi(\sqrt{n_i}\, F(\beta' X_i) / \sigma_\nu)$$

We may admit that, following (32) that

(44) $$Prob(TGRPT_i > 0) = Prob(\sqrt{n_i}\, F(\beta' X_i) + \sqrt{n_i}\ \varepsilon_i > 0) = \Phi(\sqrt{n_i}\, \beta' X_i / \sigma_\nu)$$

Or, following (37)

(45) $$Prob(TGRPT_i > 0) = Prob(\sqrt{n_i}\, F(\beta' X_i) + \sqrt{n_i}\ \varepsilon_i > 0) = \Phi(\sqrt{n_i}\, \Phi(\beta' X_i)/ \sigma_\nu)$$

Then, we can rely on the estimates of the previous estimations to propose sample selection corrections to an OLS regression (43) performed only for positive observations.

2. We considered (from the previous section) the estimators of $\hat{\beta}$ for each model and constructed respectively:

$$\text{YPREV1}_i = \hat{\beta}' X_i / \hat{\sigma}_\nu$$

$$\text{YPREV12}_i = \hat{\beta}' \sqrt{n_i}\, X_i / \hat{\sigma}_\nu$$

$$\text{YPREV13}_i = \begin{cases} \text{YPREV1}_i \text{ for TGRPT}_i > 0 \\ \text{YPREV12}_i \text{ for TGRPT}_i = 0 \end{cases}$$

from model (32) and, from the estimates of model (37):

$$\text{YPREV3}_i = \hat{\beta}' X_i$$

$$\text{YPREV32}_i = \sqrt{n_i}\, \Phi(\hat{\beta}' X_i)$$

$$\text{YPREV33}_i = \begin{cases} \text{YPREV3}_i \text{ for TGRPT}_i > 0 \\ \text{YPREV32}_i \text{ for TGRPT}_i = 0 \end{cases}$$

3. Our first attempt consisted on running a sample selection model considering the underlying probit on an (only) explanatory variable YPREVJ, J=1,12,13,3,32,33:

$$(46) \quad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\alpha_0 - \alpha_1 * \text{YPREVJ}_i) + \\ + \text{TGRPT1}_i \{- \log sig + \log \phi[(\sqrt{n_i}\, \text{HGRPT}_i - \gamma' \sqrt{n_i}\, Z_i)/ sig] \\ + \log\Phi\{\alpha_0 + \alpha_1 * \text{YPREVJ}_i + ro\, [(\sqrt{n_i}\, \text{HGRPT}_i - \gamma' \sqrt{n_i}\, Z_i)/ sig]\, (1 - ro^2)^{-0.5}\}$$

The estimate of α_1, the coefficient of YPREVJ, was usually insignificant – and significantly different from 1. Such restricted model describes a threshold binary explanation of strike incidence:

$$(47) \quad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\alpha_0 - \text{YPREVJ}_i) + \\ + \text{TGRPT1}_i \{- \log sig + \log \phi[(\sqrt{n_i}\, \text{HGRPT}_i - \gamma' \sqrt{n_i}\, Z_i)/ sig] \\ + \log\Phi\{\alpha_0 + \text{YPREVJ}_i + ro\, [(\sqrt{n_i}\, \text{HGRPT}_i - \gamma' \sqrt{n_i}\, Z_i)/ sig]\, (1 - ro^2)^{-0.5}\}$$

Finally, consistent with the modelling of TGRPT we further restricted α_0 to be 0:

$$(48) \quad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(\text{-YPREVJ}_i) +$$
$$+ \text{TGRPT1}_i \{- \log \text{sig} + \log \phi[(\sqrt{n_i}\ \text{HGRPT}_i - \gamma' \sqrt{n_i}\ Z_i)/ \text{sig}]$$
$$+ \log\Phi\{\text{YPREVJ}_i + \text{ro}\ [(\sqrt{n_i}\ \text{HGRPT}_i - \gamma' \sqrt{n_i}\ Z_i)/ \text{sig}]\ (1 - \text{ro}^2)^{-0.5}\}$$

Summary statistics of the three models, for each YPREVJ considered are in Table 22 (BHHH – Berndt *et a*l - standard deviations reported).

In general, the unrestricted probit, (46), performed badly, with the implicit estimate of ro going to 1. Restricted versions – (47) and (48) - generated a consistent estimate of SIGMA of around 65-70, and of RO around 0.3-0.6 (in most cases), even if with very low significance.

Versions with YPREVJ = YPREV12 and YPREV32 had computational problems – singularity or others.

Table 22

		(46)	(47)	(48)
YPREV1	RO	0.999796 (72.0721) [0.989]	0.549413 (0.922095) [0.551]	0.322504 (0.291404) [0.268]
	SIGMA	113.362 (37.5013) [0.003]	68.2258 (22.5279) [0.002]	66.1595 (18.7152) [0.000]
	LOGL	-142.913	-149.221	-228.837
YPREV12	RO	0.990976 (26.9411) [0.971]	0.011082 (0.085803) [0.897]	0.038 (0.446307) [0.932]
	SIGMA	81.2911 (31.4185) [0.010]	65.8997 (20.6170) [0.001]	132.200 (35.6641) [0.000]
	LOGL	-139.459	-2710.22	-9344.98
YPREV13	RO	0.999655 (0.895273E+7) [1.00]	0.571570 (1.11412) [0.608]	0.322504 (0.291404) [0.268]
	SIGMA	109.615 (235064) [1.00]	67.7092 (21.8018) [0.002]	66.1595 (18.7152) [0.000]
	LOGL	-140.317	-142.574	-228.644
YPREV3	RO	0.999771 (73.4733) [0.989]	0.712153 (0.672817) [0.290]	0.319458 (0.291300) [0.273]
	SIGMA	113.383 (37.5022) [0.002]	70.1147 (23.4196) [0.003]	66.1128 (18.6962) [0.000]
	LOGL	-142.915	-148.722	-229.226
YPREV32	RO	1.00000 (108.532) [0.993]	0.419950 (0.354283) [0.236]	0.5 (1.15987) [0.666]
	SIGMA	104.718 (33.5102) [0.002]	66.5699 (20.3266) [0.001]	66.2642 (20.4117) [0.001]
	LOGL	-141.397	-225.915	-249.180
YPREV33	RO	0 (x) [x]	0.456884 (0.414969) [0.271]	0.319458 (0.291300) [0.273]
	SIGMA	66.1029 (19.9912) [0.001]	68.7195 (21.1531) [0.001]	66.1128 (18.6962) [0.000]
	LOGL	-128.974	-327.917	-346.719

4. Finally, we considered for the non-zero observations only, an Heckman-type correction, constructing the inverse Mills ratio for each YPREVJ:

$$\text{(49)} \qquad \lambda J_i \;=\; \lambda(YPREVJ_i) = \frac{\phi(YPREVJ_i)}{\Phi(YPREVJ_i)}$$

and ran $\qquad \sqrt{n_i}\,\mathrm{HGRPT}_i \;=\; \gamma' \sqrt{n_i}\,Z_i \;+\; \rho\,\sigma_\mu\,\lambda J_i \;+\; \mu_i\,,$

$$\text{(50)} \qquad \sqrt{n_i}\,\mathrm{HGRPT}_i \;=\; \gamma' \sqrt{n_i}\,Z_i \;+\; \lambda_\mu\,\lambda J_i \;+\; \mu_i$$

Computations of standard deviations of (50) were corrected for heteroscedasticity. Theoretically, (50) would be comparable to – or reproduce a la Heckman - (48).

The arguments of λ(.) in (49) were corrected with the estimated arguments of probits of TGRPT1 on YPREVJ – that is, from regressions of type (46), the unrestricted linear probit; and also (47), the probit with a constant term and the coefficient of YPREVJ restricted to be equal to 1 (the threshold model of TGRPT1 on each YPREVJ).

The estimated coefficients in regressions of type (50) for the three alternatives are reported in Table 23.

(We essayed weighting the inverse Mills ratio, λJ, by $\sqrt{n_i}$, but its significance was, in general, lower.)

Table 23

		UNRPROBIT	RESTPROBIT	λ(YPREVJ)
LAM1	Coef.	247.760 (121.295) [0.064]	69.6135 (41.5099) [0.119]	20.9682 (14.7806) [0.181]
	SIGU	81.4885	88.2643	87.5072
	RO	3.040429	0.788694	0.239616
	RBAR2	0.682097	0.630254	0.635133
LAM12	Coef.	124.812 (47.9365) [0.023]	0.713523 (8.25606) [0.933]	3.64998 (9.48163) [0.707]
	SIGU	80.0893	91.2338	90.8930
	RO	1.558410	0.00782082	0.040157
	RBAR2	0.692903	0.612851	0.614010
LAM13	Coef.	215.781 (133.194) [0.131]	98.1925 (46.5183) [0.056]	20.9682 (14.7806) [0.181]
	SIGU	86.6530	87.9900	87.5072
	RO	2.490173	1.115951	0.239617
	RBAR2	0.641641	0.632592	0.635133
LAM3	Coef.	246.976 (121.457) [0.065]	68.3328 (40.1250) [0.114]	20.7483 (14.5987) [0.181]
	SIGU	81.5571	88.2496	87.5276
	RO	3.028259	0.774313	0.237049
	RBAR2	0.681558	0.630383	0.634982
LAM32	Coef.	89.1820 (97.2757) [0.377]	14.0895 (28.0579) [0.625]	56.5199 (80.4158) [0.496]
	SIGU	89.0758	90.6231	90.0743
	RO	1.001192	0.155474	0.627481
	RBAR2	0.623588	0.614023	0.617993
LAM33	Coef.	21.4455 (15.3512) [0.188]	27.4160 (21.5852) [0.228]	20.7483 (14.5987) [0.181]
	SIGU	87.6769	88.4168	87.5276
	RO	0.244596	0.310077	0.237049
	RBAR2	0.633874	0.628523	0.634982

Except for LAM33, the significance of the inverse Mills ratio was higher when it was derived from the unrestricted probits of TGRPT1 on YPREVJ. Yet, the best regressions implied an estimate of RO slightly above one.

5. We report in Table 24 below the estimates of the coefficients for versions involving YPREV3 – the restricted sample selection model of the second column of Table 22 and the two-step Heckman-type estimators of second column of Table 23 (the two models have similar philosophy).

Table 24		
Independent Variables	(47) YPREV3	RESTPROBIT
CONSTANT	-0.826018 (0.498536) [0.098]	-0.852039 (0.505527) [0.118]
IG	-0.202458 (1.07622) [0.851]	-0.355738 (1.38341) [0.801]
DIMEMP	0.00173578 (0.00304698) [0.569]	0.00181922 (0.000559314) [0.007]
TSIND	0.00562263 (0.00820838) [0.493]	0.00630460 (0.00504276) [0.235]
DTCOCI	-0.016473 (0.014863) [0.268]	-0.019988 (0.015050) [0.209]
ANTIG	0.105620 (0.091898) [0.250]	0.113102 (0.057723) [0.074]
DIDADE	-0.144280 (0.319915) [0.652]	-0.130252 (0.127806) [0.328]
TRTNIPC	0.019768 (0.030151) [0.512]	0.022223 (0.028462) [0.450]
VABT	-0.0000757592 (0.0000626588) [0.227]	-0.0000913324 (0.0000571225) [0.136]
PINTC	0.013687 (0.012153) [0.260]	0.014724 (0.012385) [0.257]
SSE		93455.9
RBAR2		0.630383
F-TEST		4.70010 [0.007]
Log Likelihood	-148.722	-128.198

Comparing with (the second column of) Table 12, signs effects stood the change in modeling, even if significance deteriorated. Restricting both forms, we arrived at versions in Table 25. Significance of Heckman´s type estimators is higher. Industry concentration and proportion of part-time employment were dropped in both forms.

Table 25		
Independent Variables	(47) YPREV3	RESTPROBIT
CONSTANT	-0.601630 (0.474607) [0.205]	-0.587628 (0.355468) [0.121]
DIMEMP	0.00187880 (0.00174787) [0.282]	0.00183912 (0.000335771) [0.000]
TSIND		0.00667717 (0.00266070) [0.025]
DTCOCI		-0.017558 (0.012148) [0.170]
ANTIG	0.116746 (0.044424) [0.009]	0.082808 (0.037927) [0.047]
DIDADE		-0.125074 (0.113730) [0.290]
VABT	-0.000108095 (0.0000438509) [0.014]	-0.0000922594 (0.0000552291) [0.117]
PINTC	0.00947344 (0.010717) [0.377]	0.010775 (0.00893253) [0.248]
RHO	0.995194 (0.093706) [0.000]	0.891009
SIGMA	95.8023 (25.8327) [0.000]	85.6619
LAM3		76.3255 (40.0343) [0.077]
SSE		102732
RBAR2		0.657154
F-TEST		6.07742 [0.002]
Log Likelihood	-151.365	-129.286

6. Summary and Conclusions.

Summarizing:

1. We advanced a simple explanation of strike behavior based on signalling motives by workers without the use of bargaining structures. Spence-type models were advanced, with strikes, through which individuals-workers "burn" their time, originating the possibility of a separating equilibrium. For this situation to occur, the most productive workers must prefer longer hours – or have a higher preference for income relative to leisure – and would be the group that strikes.

Two basic models were advanced: in one, firms are able to monitor and enforce hours and offer different workweeks to the two types of workers (a previous part-time/full-time wage schedules separating equilibrium was presented). In the other, only one work-week schedule can be offered.

2. Empirical evidence was designed to explain strike incidence, measured by the proportion of strikers observed in each sector, and strike severeness, proxied by a measure of mean strike hours lost per worker in each industry.

Industry concentration dissuades striking – more highly concentrated sectors provide higher wage growth as higher wages; (hence,) strike disputes are more rare and terminate more quickly.

A positive firm size effect was encountered more often than the industry concentration one, suggesting a link to monitoring problems. Tenure length seems to affect strike activity positively.

Empirical evidence on the effect of part-time employment and variance of weekly hours on strike occurrence offer some support to the proposed theoretical imperfect information models. Nevertheless, aggregate approaches – tested in Appendix 3 – would not clearly point to strikes as arising from a purely individual decision-type process, as the models here presented would suggest; but they also reject – for the case of Portugal – firms as the relevant bargaining units.

Unionisation has a positive effect on strike occurrence, as expected, but not always significant.

Time series empirical evidence seems to indicate that strike activity is procyclical – in troubled times, workers restrain from disruptive bargaining. However, cross-section evidence presented in the paper suggests that, all else controlled for, strike occurrence and severeness vary inversely with sector dynamism (eventually, increase as product life-cycle goes on). Consistently, labor productivity (in valued-added terms) decreases strike incidence, even if this could have been explained by other factors, alluded in the text.

Another persistent finding was a positive effect from the increase in the use of intermediate products in the sector on strike activity – interpreted as higher substitution/tability by other inputs decreasing the opportunity costs of and inducing strikes.

Residuals from settled base wage regressions had a negative impact on strike equations, as expected – higher wage than the “trend” decreasing strikes - but not always significant, which could be explained by indirect effects being already included or other earnings or non-pecuniary factors important in the bargaining process.

3. Strike occurrence and length were modelled in a weighted least squares linear model and with limited dependent variables approaches. The latter involved the enlargement of grouped data methodologies to deal with zero observations of the dependent variable. In what concerns strike occurrence, the approach followed in the text can be visualized as extended TOBIT´s applied to minimum chi-square estimators. Strike severeness – average strike length – was modelled in a sample selection framework and as an extension of Heckman´s two-step procedure.

Other methods to deal with zero observations for the dependent variable of binary choice models that use mean data were also proposed; they involve stronger non-linearity than minimum chi-square extensions. They may be useful in studies that have to rely on mean or grouped data.

4. The estimation procedures used 30 observations and over-aggregation may imply severe bias in the results. Additionally, the construction of sector indicators used sources with different classifications, correspondence being achieved by numeric (rough) approximations. Simultaneous (in time) data for all the variables involved was also lacking. Further study would be needed to justify the results found, even if most are consistent with evidence found for other countries, or that we would expect or explain from theoretical considerations.

Appendix 1: Data and Sources

A. Variables

(Growth rates were usually defined in percentage terms.)

G94T – Total Number of Strikes (Table 8, “Conflitos Colectivos de Trabalho, Anual 1994.)

NT94T – Number of Workers on Strike (Table 11, “Conflitos Colectivos de Trabalho, Anual 1994”.)

ND94T – Work Days Lost Due to Strike (Table 11, “Conflitos Colectivos de Trabalho, Anual 1994”.)

TCOCI –Number of Partial Time and Full-Time Workers in the industry (Table 45, “Quadros de Pessoal”, 1994.)

TCOC –Number of Full-Time Workers in the industry (Table 47, “Quadros de Pessoal”, 1994.)

EMP – Industry Employment, Individuals, Total (From Table 2.2.1, “Contas Nacionais”, 1994 and 1993, thousands.)

EMPR – Industry Employment, Individuals, Paid (From Table 2.2.1, “Contas Nacionais”, 1994 and 1993, thousands.)

HNTCOCI – Average Standard Work Week Hours, Partial Time and Full-Time Workers, (Table 50, “Quadros de Pessoal”, 1994.)

HNTCOC – Average Standard Work Week Hours, Full-Time Workers, (Table 51, “Quadros de Pessoal”, 1994.)

HTTCOCI – Average Total Work Week Hours, Partial Time and Full-Time Workers (Table 52, “Quadros de Pessoal”, 1994.)

TRTNIPC = 100 – 100*(TCOC*HNTCOC)/ (TCOCI*HNTCOCI) – proportion (percentage) of partial time hours out of the total hours

PTCO – Percentage of Workers Not Self-Employed Relative to Industry Total (Table 29, “Quadros de Pessoal”, 1994.)

PECCP – Proportion (Percentage) of Permanent Employment Contracts in Total Industry Employment (From Tables 6 and 8, “Inquérito ao Emprego”, 1994.)

HGRPT = 8 * ND94T / TCOCI – approximate number of hours of strike per worker in the industry

HGRPC = HGRPT / HTTCOCI – (approximately) proportional to the proportion of strike hours over work hours in the industry

TGRPT = NT94T / TCOCI – proportion of workers in the industry that were involved in a strike during the year

NTD94T = ND94T / NT94T – approximate number of days lost per worker on strike in the industry

HGRS = 8 * NTD94T – approximate number of hours lost per worker on strike in the industry

HNAOT93 - proportion (percentage) of hours of absenteeism and temporary inactivity out of the total hours effectively worked by 1-digit CAE industry (From Table 29, "Balanço Social, 1993.)

HNAAT93 - proportion (percentage) of absenteeism in the sector due to work accidents by 1-digit CAE industry (From Table 29, "Balanço Social, 1993.)

HNADN93 - proportion (percentage) of absenteeism in the sector due to non-professional disease by 1-digit CAE industry (From Table 28, "Balanço Social, 1993.)

HNADP93 - proportion (percentage) of absenteeism in the sector due to professional disease by 1-digit CAE industry (From Table 28, "Balanço Social, 1993.)

HNASD93 - proportion (percentage) of absenteeism in the sector due to disciplinary suspension by 1-digit CAE industry (From Table 28, "Balanço Social, 1993.)

HNAAI93 - proportion (percentage) of absenteeism in the sector due to undelayable assistance by 1-digit CAE industry (From Table 28, "Balanço Social, 1993.)

HNAMP93 - proportion (percentage) of absenteeism in the sector due to maternity/paternity assistance by 1-digit CAE industry (From Table 28, "Balanço Social, 1993.)

HNAOC93 - proportion (percentage) of absenteeism in the sector due to other causes by 1-digit CAE industry (From Table 28, "Balanço Social, 1993.)

ANAAT93 = HNAAT93 * HNAOT93 /100

ANADN93 = HNADN93 * HNAOT93 /100

ANADP93 = HNADP93 * HNAOT93 /100

ANASD93 = HNASD93 * HNAOT93 /100

ANAAI93 = HNAAI93 * HNAOT93 /100

ANAMP93 = HNAMP93 * HNAOT93 /100

ANAOC93 = HNAMP93 * HNAOT93 /100

TSIND – Union density in (average for the period, percentage) 1991-1995 (From Table 9, Cerdeira (1997).)

TSIND1 – Union density in (average for the period, percentage) 1991-1995 (From Table A2, Cerdeira (1997).)

REMBASE – Standard Work Monthly Base-Wages (Table 63, "Quadros de Pessoal", 1994, Portuguese escudos)

GANHO – Total Monthly Earnings (Table 64, "Quadros de Pessoal", 1994, Portuguese escudos)

REMHOR – Standard Work Hourly Base-Wages (Table 73, "Quadros de Pessoal", 1994, Portuguese escudos)

REMTC – Growth Rate of Standard Work Monthly Base-Wages between 1993 and 1994.

GATC - Growth Rate of Total Monthly Earnings between 1993 and 1994.

REMHTC - Growth Rate of Standard Work Hourly Base-Wages between 1993 and 1994.

RET – Annual Wages and Salaries per Employed Individual (From Tables 2.1.1.1.2 and 2.2.1, "Contas Nacionais", 1994, thousand Portuguese escudos)

RETE – Annual Wages and Salaries per Paid Employed Individual (From Tables 2.1.1.1.2 and 2.2.1, "Contas Nacionais", 1994, thousand Portuguese Escudos)

RETTC – Growth Rate of Wages and Salaries per Employed Individual (From Tables 2.1.1.1.2 and 2.2.1, "Contas Nacionais", 1993 and 1994.)

RETETC – Growth Rate of Wages and Salaries per Paid Employed Individual (From Tables 2.1.1.1.2 and 2.2.1, "Contas Nacionais", 1993 and 1994.)

HCI – Average of Standard Work Week Hours, Partial Time and Full-Time Workers (From Table 45, "Quadros de Pessoal", 1994, assigning at class:

Less than 15 hours – 10 hours
15-30 hours – 22.5 hours
30-35 hours – 32.5 hours
35-40 hours – 37.5 hours
40-44 hours – 42 hours
44-48 hours – 46 hours
48 and more – 50 hours. The same points were considered for the construction of a proxy of variance of weekly hours in the industry HCIVAR and HCVAR.)

HCIVAR – App. Variance of Standard Work Week Hours, Partial Time and Full-Time Workers (From Table 45, "Quadros de Pessoal", 1994.)

HCISIG = square root of HCIVAR

HCICV = HCISIG / HCI (coefficient of variation)

HC – Average of Standard Work Week Hours, Full-Time Workers (From Table 47, "Quadros de Pessoal", 1994, as in HCI.)

HCVAR – App. Variance of Standard Work Week Hours, Full-Time Workers (From Table 47, "Quadros de Pessoal", 1994.)

HCSIG = square root of HCVAR

HCCV = HCSIG / HC (coefficient of variation)

TXDES – Industry Unemployment Rate (From Tables 6 and 27, "Inquérito ao Emprego", 1994, percentage)

TXDESH – Male Industry Unemployment Rate (From Tables 6 and 27, "Inquérito ao Emprego", 1994, percentage)

TXDESM – Female Industry Unemployment Rate (From Tables 6 and 27, "Inquérito ao Emprego", 1994, percentage)

DTXDES – Change in TXDES from 1993 to 1994.

DTXDESH – Change in TXDESH from 1993 to 1994.

DTXDESM – Change in TXDESM from 1993 to 1994.

DTCOCI – Growth rate of sector total employment (i.e. of TCOCI) from 1993 to 1994.

DTCOC – Growth rate of sector full time employment (i.e. of TCOC) from 1993 to 1994.

EMPTC – Growth rate of sector employment (i.e., of EMP) from 1993 to 1994.

EMPRTC – Growth rate of paid sector employment (i.e., of EMPR) from 1993 to 1994.

TCEX – Percentage of Workers With Overtime Relative to Industry Total (Table 55, "Quadros de Pessoal", 1994.)

HTCEX – Average Hours Length of Weekly Overtime Work (Table 56, "Quadros de Pessoal", 1994.)

HEXTPTR = TCEX * HTCEX / 100 – Weekly Overtime Hours per Worker Employed

HEXTPC = 100 * HEXTPTR / HTTCOCI – Proportion (percentage) of overtime hours over the total hours in the industry

DTCEX – Change in TCEX from 1993 to 1994.

DHTCEX – Change in HTCEX from 1993 to 1994.

DHEXTPT – Change in HEXTPTR from 1993 to 1994.

DHEXTPC – Change in HEXTPTC from 1993 to 1994.

DTRTN - Change in TRTNIPC from 1993 to 1994.

DPECCP - Change in PECCP from 1993 to 1994.

VAB – Industry Gross Value Added (From Table 2.1.1.1.2, "Contas Nacionais", 1994 and 1993, million Portuguese escudos)

VABTC – Growth Rate of the Industry Gross Value Added (From Table 2.1.1.1.2, "Contas Nacionais", 1994 and 1993.)

PEFTC – Growth Rate of the Industry Effective Production (From Table 2.1.1.1.2, "Contas Nacionais", 1994 and 1993.)

PINTC – Growth Rate of the Industry Intermediate Consumption (From Table 2.1.1.1.2, “Contas Nacionais”, 1994 and 1993.)

VABRTC – Growth Rate of the Industry Real Gross Value Added (From Tables 2.1.1.1.2 and 2.1.1.2.2, “Contas Nacionais”, 1994 and 1993.)

PEFRTC – Growth Rate of the Industry Real Effective Production (From Tables 2.1.1.1.2 and 2.1.1.2.2, “Contas Nacionais”, 1994 and 1993.)

PINRTC – Growth Rate of the Industry Real Intermediate Consumption (From Table 2.1.1.1.2, “Contas Nacionais”, 1994 and 1993.)

VABPTC – Growth Rate of the Industry Gross Value Added Price (From Tables 2.1.1.1.2 and 2.1.1.2.2, “Contas Nacionais”, 1994.)

PEFTPC – Growth Rate of the Industry Effective Production Price (From Tables 2.1.1.1.2 and 2.1.1.2.2, “Contas Nacionais”, 1994.)

PINPTC – Growth Rate of the Industry Intermediate Consumption Price (From Table 2.1.1.1.2, “Contas Nacionais”, 1994 and 1993.)

REMVA - Wage Bill Share (From Table 2.1.1.1.2, “Contas Nacionais”, 1994, percentage.)

VEVA – Changes in Stocks over Gross Value Added, (From Tables 2.1.1.2.1 and 2.1.1.1.2, “Contas Nacionais”, 1994.)

AVEVA – Absolute Changes in Stocks over Gross Value Added, (From Tables 2.1.1.2.1 and 2.1.1.1.2, “Contas Nacionais”, 1994.)

VEPE – Changes in Stocks over Effective Production, (From Tables 2.1.1.2.1 and 2.1.1.1.2, “Contas Nacionais”, 1994.)

AVEPE – Absolute Changes in Stocks over Effective Production, (From Tables 2.1.1.2.1 and 2.1.1.1.2, “Contas Nacionais”, 1994.)

VABT = VAB / EMP – Gross Value Added per Employed Individual (thousand Portuguese escudos).

VABTE = VAB / EMPR – Gross Value Added per Paid Employed Individual (thousand Portuguese escudos).

VABTTC – Growth Rate of Gross Value Added per Employed Individual, i.e., of VABT.

VABTETC – Growth Rate of Gross Value Added per Paid Employed Individual, i.e., of VABTE.

VABRTTC – Growth Rate of Real Gross Value Added per Employed Individual.

VABRTET – Growth Rate of Real Gross Value Added per Paid Employed Individual.

EDUC – Average years of education of workers employed in the industry (From Table 30, “Quadros de Pessoal”, 1994, assigning

Inferior ao 1º Ciclo – 2 years
Habilitados com o 1º Ciclo – 4 years
Habilitados com o 2º Ciclo – 6 years
Habilitados com o 3º Ciclo – 9 years
Ens. Sec. Cursos e Escolas Profissionais – 12 years
Bacharelato – 15 years
Licenciatura – 17 years.)

EDUC1 – Average years of education of workers employed in the industry (From Table 30, “Quadros de Pessoal”, 1994, assigning

Inferior ao 1º Ciclo – 2 years
Habilitados com o 1º Ciclo – 4 years
Habilitados com o 2º Ciclo – 6 years
Habilitados com o 3º Ciclo – 9 years
Ens. Sec. Cursos e Escolas Profissionais – 11 years
Bacharelato – 14 years
Licenciatura – 16 years.)

ANTIG – Average years of tenure of workers employed in the industry (From Table 32, “Quadros de Pessoal”, 1994, assigning

Less than 1 year – 0.5 years
1 to 4 years – 2.5 years
5 to 9 years – 7.5 years
10 to 14 years – 12.5 years
15 to 19 years – 17.5 years
20 and more years – 27.5 years.)

IDAD - Average age of workers employed in the industry (From Table 41, “Quadros de Pessoal”, 1994, assigning

Less than 15 years – 14 years
15 to 24 years – 20 years
25 to 34 years – 30 years
35 to 44 years – 40 years
45 to 54 years – 50 years
55 to 64 years – 60 years
65 and more years – 70 years.)

PCMQP – Proportion (percentage) of Women in Industry Employment (From Tables 35 and 37, “Quadros de Pessoal”, 1994.)

PCEM – Proportion (percentage) of Women in Industry Employment (From Table 8, “Inquérito ao Emprego”, 1994.)

DIMEMP – Average firm size in the industry in number of workers employed (From Tables 9 and 11, “Quadros de Pessoal”, 1994.)

DIMEST – Average plant size in the industry in number of workers employed (From Tables 13 and 15, “Quadros de Pessoal”, 1994.)

ESTEMP – Average number of plants per firm in the industry (From Tables 11 and 13, "Quadros de Pessoal", 1994.)

IG – Industry concentration measured by the Ginni coefficient on the distribution of employment by firm size (From Tables 9 and 11, "Quadros de Pessoal", 1994.)

HI – Industry concentration measured by an approximation to the Herfindhal index on the distribution of employment by firm size (From Tables 9 and 11, "Quadros de Pessoal", 1994.)

PCTR9 – Proportion (percentage) of workers in the industry in firms with less than 10 workers (From Tables 9 and 11, "Quadros de Pessoal", 1994.)

PCTR200 – Proportion (percentage) of workers in the industry in firms with 200 workers or more (From Tables 9 and 11, "Quadros de Pessoal", 1994.)

PCTR500 - Proportion (percentage) of workers in the industry in firms with 500 workers or more (From Tables 9 and 11, "Quadros de Pessoal", 1994.)

B. Observations

The observation classification comes from CAE "Classificação de Actividades Económicas" used in Quadros de Pessoal and Greves for 1994 (the classification changed in more recent years). Union density, data on unemployment, on industry product and production were available with a slight change in categories and sector correspondence had to be made.

1 – Agriculture and Quarry
2 – Forestation
3 – Fishing
4 – Coal Mining
5 – Metallic Ore Mining
6 – Non Metallic Ore Mining
7 – Food, Beverages and Tobacco Manufacturing Industries
8 – Textiles, Clothing and Leather
9 – Wood and Cork Manufacturing Industries
10 – Paper, Graphical Arts and Publishing
11 – Chemical Industries from Oil and Coke, and Rubber and Plastic Manufactures
12 – Non Metallic Ore Manufacturing
13 – Heavy Metallurgy
14 – Metallic Products, Machinery and Transportation Material Manufacturing
15 – Other Manufacturing Industries
16 – Electricity, Gas Fuel, and Steam
17 – Water Supply
18 – Construction and Public Infrastructure
19 – Wholesale Trade
20 – Retail Trade
21 – Restoration and Lodging
22 – Transportation and Storage
23 – Communications
24 – Banking and Other Monetary and Financial Institutions
25 – Insurance

26 – Real Estate and Service to Firms
27 – Sanitation and Cleaning
28 – Social Services
29 – Recreation and Cultural Activities
30 – Personal and Domestic Services
31 – Overall economy average (corresponding to Multi-Sector Strikes in the Strike variables)

Appendix 2: Descriptive Statistics

A. Mean and Dispersion (30 observations: weight=TCOCI, TCOCI93)

Table A.1

	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
G94T	9.73333	20.04638	19.10528	29.415	0	106
G93T	7.40000	11.72266	14.16344	16.00502	0	46
NT94T	2087.1000	3858.1893	3356.65164	5152.5573	0	17667
NT93T	2001.6000	5164.56818	3899.6134	7141.7452	0	21894
ND94T	2497.5333	3843.70913	3931.1171	4517.01477	0	13468
ND93T	2229.43333	4853.78231	5327.02114	6907.5406	0	18348
HGRPT	0.48343	0.82607	0.32506	0.56094	0	3.04818
HGRPT93	0.30557	0.49577	0.29012	0.39524	0	1.65639
HGRS	9.63022	9.26032	11.85265	8.10041	0	40.25999
HGRS93	9.15693	9.26114	14.39393	11.21213	0	30.45242
TGRPT	0.052270	0.095197	0.033955	0.060543	0	0.37355
TGRPT93	0.041425	0.080471	0.032559	0.062361	0	0.33021
TSIND	42.03333	26.40074	39.40753	25.38171	13	106
TSIND1	42.57000	26.11757	39.50805	25.23970	13.4	105.5

Table A.2						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
REMBASE	104162.5000	30036.31297	95471.3969	26002.65263	64871	167557
GANHO	128177.3000	46565.45716	111901.11647	39149.31335	70228	234374
REMHOR	622.73333	216.00238	556.90568	185.57369	363	1157
REMTC	8.17930	4.78394	8.09964	2.15634	-8.64157	23.14266
GATC	10.17445	7.21841	9.12710	2.51067	-7.58493	40.97554
REMHTC	12.25438	6.39396	11.36762	2.92887	-0.70258	37.53666

Table A.3						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
HCI	36.85336	3.04011	37.83108	2.37510	25.24587	39.71698
HCIVAR	39.46644	28.16236	40.02415	19.44765	6.57779	120.01115
HCISIG	5.91098	2.16399	6.16428	1.44764	2.56472	10.95496
HCICV	0.16361	0.074988	0.16470	0.050737	0.072289	0.43393
HC	38.69108	2.29324	39.48194	1.86172	32.663	41.39959
HCVAR	8.22453	5.58146	8.80756	5.16652	0.36186	29.45177
HCSIG	2.70763	0.96129	2.88302	0.71612	0.60155	5.42695
HCCV	0.069776	0.025004	0.073319	0.020041	0.016061	0.14690

Table A.4						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
HNTCOCI	37.34000	3.04921	38.33705	2.45968	25.8	40.3
HNTCOC	39.24000	2.30511	40.02260	1.93777	33.2	42.2
HTTCOCI	37.79000	3.16362	38.64619	2.52467	25.8	41
DHNTCCI	-1.19333	1.24815	-1.08243	0.62941	-5.4	1.1
DHNTCC	-1.42667	1.14106	-1.26627	0.75457	-5	0.3
DHTTCCI	-1.04333	1.32501	-1.04962	0.85173	-5.5	1.6
TRTNIPC	6.72038	7.74941	5.69306	5.05063	1.51808	43.367
PTCO	94.26667	4.67321	92.73073	4.76889	83.9	100
PECCP	89.52760	4.33628	89.30272	3.76851	76.842	95.178

Table A.5						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
TXDES	6.30450	2.76634	6.94678	2.23317	2.388	13.58
TXDESH	5.42323	2.24089	5.97368	2.04058	1.599	8.984
TXDESM	7.89857	7.43739	8.68016	3.39515	0	39.394
DTCOCI	-2.45150	10.13849	0.48482	7.34508	-28.59639	16.77750
DTCOC	-0.15518	10.62513	1.86316	6.96355	-29.56012	20.18615
EMPTC	-1.70579	3.49792	-0.69717	1.88700	-13.15790	4.15094
EMPRTC	-2.48825	4.16263	-1.76180	2.90423	-14.22523	3.57143
TCEX	9.39667	9.62373	7.30140	6.55567	0.3	36.9
HTCEX	4.79333	1.33182	4.32572	1.18917	2.7	7.1
HEXTPTR	0.46310	0.60099	0.34173	0.42741	0.015	2.6199
HEXTPC	1.19574	1.49951	0.87154	1.04631	0.037879	6.50099

Table A.6						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
VABTC	8.28278	18.00265	6.80990	18.42939	-29.63226	74.89391
PEFTC	10.25968	13.70706	10.46743	13.15439	-23.37992	60.94920
PINTC	13.47119	12.21508	16.13623	8.71192	-20.93485	42.72865
VABRTC	-2.15672	18.82916	-0.91008	18.75697	-47.54450	66.68447
PEFRTC	3.43428	14.16903	4.24652	13.69721	-39.86690	53.93120
PINRTC	9.12990	10.92800	11.64886	8.02670	-21.70244	34.04514
VABPTC	12.43515	19.07556	8.63610	11.13850	0.54252	103.91426
PEFPTC	6.96687	5.39393	6.30652	4.82232	1.06675	27.41748
PINPTC	3.92017	2.35383	4.01444	1.85920	0.65774	11.13307
VABT	4941.04512	4329.77487	3935.33447	2553.51580	-162.07408	17309.97070
VABTE	6860.29885	6959.80520	5382.10243	3271.98448	-162.07408	35360.69141
VABTTC	10.13038	17.34094	7.55817	18.24756	-29.46737	72.4822
VABTETC	11.17083	18.22925	8.79896	18.49692	-30.09521	69.39410
VABRTTC	-0.50950	18.29243	-0.22798	18.56677	-47.22562	64.38596
VABRTTEC	0.43843	18.99981	0.92175	18.72942	-47.22562	61.44283
REMVA	-68.45009	610.54897	11.84852	314.41135	-3299.17725*	84.19576
REMVA (29)	42.95429	21.39446	40.63552	15.99284	2.49352	84.19576

* For sector 25, Insurance, a negative value was registered; hence we report statistics without it as well, in rows REMVA (29).

Table A.7						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
EDUC	6.68625	1.69753	6.62674	1.55791	4.37859	10.92794
EDUC1	6.50727	1.55766	6.45824	1.42391	4.35248	10.36629
ANTIG	9.37632	4.32151	8.20610	3.03643	3.02299	19.21743
IDAD	37.77392	3.06920	36.00541	2.94132	31.88510	44.27486
PCMQP	32.93190	20.18235	40.61526	21.28713	4.99040	88.22330
PCEM	34.05583	23.23956	40.14433	23.42530	4.805	75.519

Table A.8						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
DIMEMP	90.99889	246.69418	51.46518	185.69346	4.75929	1307.96558
DIMEST	21.51585	17.78567	16.95579	12.14812	4.50725	75.14286
ESTEMP	2.63200	4.24393	1.86700	3.09658	1	19.13793
IG	0.49555	0.25866	0.42850	0.19318	0.11885	0.98943
HI	0.10230	0.24433	0.013155	0.055916	0.00037149	0.90041
PCTR9	18.77756	17.75241	21.99079	16.99463	0.16345	59.50191
PCTR200	39.27215	32.30905	30.48934	22.15703	0	98.59745
PCTR500	26.65870	32.37419	19.67715	22.12706	0	97.69582

Table A.9						
	Mean	Std Dev	W. Mean	W Std Dev	Minimum	Maximum
HNAOT93	9.55000	1.82355	9.52896	1.76599	6.0	11.4
ANAAT93	0.83237	0.57241	0.73620	0.30139	0.19200	2.31420
ANADN93	5.43883	1.13095	5.26156	1.09293	3.39660	7.04080
ANADP93	0.029870	0.037741	0.028780	0.030781	0	0.11850
ANASD93	0.023813	0.020834	0.025416	0.019547	0	0.089600
ANAAI93	0.19664	0.10517	0.21733	0.10722	0.059200	0.33300
ANAMP93	0.39156	0.18632	0.44864	0.17705	0.066600	0.59940
ANAOC93	2.62297	0.66788	2.79328	0.60642	1.65900	4.00960

B. Simple Correlations

Table B.1

1993 1994	GT	NTT	NDT	HGRPT	HGRS	TGRPT	TSIND	TSIND1
GT	1	0.77614 *	0.85747 *	0.52406 *	0.25924	0.52355 *	0.10647	0.093127
NTT	0.88033 *	1	0.91637 *	0.55374 *	-0.010664	0.53109 *	0.24410	0.23984
NDT	0.66703 *	0.85347 *	1	0.48403 *	0.22364	0.41163 *	0.15769	0.14947
HGRPT	0.13284	0.47153 *	0.63253 *	1	-0.0028128	0.95847 *	0.14844	0.13749
HGRS	0.035821	-0.0034449	0.28083	0.15380	1	-0.10237	-0.33442 **	-0.35866 *
TGRPT	0.21795	0.50577 *	0.50088 *	0.92846 *	-0.023398	1	0.19938	0.19162
TSIND	0.14720	0.34782 **	0.28682	0.41090 *	0.0018694	0.45283 *	1	0.99615 *
TSIND1	0.13924	0.34143 **	0.27736	0.42192 *	-0.010960	0.46543 *	0.99615 *	1

Table B.2

	G93T	NT93T	ND93T	HGRPT93	HGRS93	TGRPT93
G94T	0.83144 *	0.85535 *	0.83722 *	0.35020 **	0.10106	0.32788 **
NT94T	0.73790 *	0.88518 *	0.82938 *	0.44111 *	-0.0011126	0.43121 *
ND94T	0.66168 *	0.64198 *	0.70174 *	0.33883 **	0.12513	0.30154
HGRPT	0.22092	0.17658	0.10892	0.27393	-0.18507	0.37920 *
HGRS	0.18671	-0.021645	0.059072	-0.14151	0.25860	-0.14903
TGRPT	0.30735 **	0.27876	0.18084	0.37157 *	-0.22703	0.51520 *

Table B.3								
	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
REMBASI	-0.070885	0.11728	0.083594	0.24132	-0.28214	0.23543	0.51577 *	0.49226 *
GANHO	-0.10725	0.10463	0.083521	0.24847	-0.35211 **	0.23432	0.50637 *	0.48543 *
REMHOR	-0.11079	0.077775	0.045106	0.22179	-0.31087 **	0.22040	0.55950 *	0.53718 *
REMTC	-0.036997	-0.010351	0.030886	-0.039652	-0.021351	-0.059164	0.069553	0.028158
GATC	-0.044511	-0.079230	-0.069505	-0.17827	-0.17082	-0.20308	-0.040849	-0.068501
REMHTC	-0.14314	-0.051504	0.011074	0.041947	-0.10013	-0.014477	0.10494	0.080505

Table B.4								
	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
HCI	0.22258	0.18465	0.21020	-0.027234	0.14152	-0.027610	-0.28768	-0.30171 **
HCIVAR	-0.064930	-0.21008	-0.26643	-0.17544	0.090681	-0.13906	-0.22483	-0.17898
HCISIG	-0.0096584	-0.17821	-0.24273	-0.19601	0.16139	-0.14612	-0.23276	-0.19204
HCICV	-0.050490	-0.18849	-0.24618	-0.15980	0.12536	-0.12072	-0.14899	-0.11412
HC	0.21689	0.059657	0.063725	-0.15507	0.26956	-0.14321	-0.53760 *	-0.52628 *
HCVAR	0.052881	-0.014421	-0.11563	-0.17223	0.032561	-0.10906	-0.032349	-0.033696
HCSIG	0.11186	0.028021	-0.074859	-0.14002	0.12558	-0.068623	-0.026228	-0.023825
HCCV	0.081309	0.018414	-0.084309	-0.11701	0.093867	-0.046850	0.060835	0.061378

Table B.5						
	REMBASE	GANHO	REMHOR	REMTC	GATC	REMHTC
HCI	-0.23380	-0.27005	-0.32273 **	0.026807	0.079999	-0.15081
HCIVAR	-0.60489 *	-0.62866 *	-0.56876 *	-0.35022 **	-0.078223	-0.40355 *
HCISIG	-0.66207 *	-0.70574 *	-0.63644 *	-0.34795 *	-0.044070	-0.45771 *
HCICV	-0.54232 *	-0.57012 *	-0.50030 *	-0.28369	-0.048762	-0.35754 **
HC	-0.78068 *	-0.81902 *	-0.85655 *	-0.22194	0.051515	-0.46920 *
HCVAR	-0.17528	-0.25374	-0.15858	0.021628	0.25967	-0.19888
HCSIG	-0.25869	-0.35143 **	-0.25804	-0.010457	0.23271	-0.22705
HCCV	-0.14735	-0.24025	-0.13425	0.036350	0.22274	-0.15955

Table B.6

	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
HNTCOCI	0.21799	0.17863	0.22350	-0.024518	0.16941	-0.039786	-0.31593 **	-0.33073 **
HNTCOC	0.18896	0.022027	0.051369	-0.16728	0.30963	-0.17299	-0.57390 *	-0.56211 *
HTTCOCI	0.22751	0.20582	0.22856	-0.030640	0.10932	-0.037402	-0.30770 **	-0.32456 **
DHNTCCI	0.11046	-0.0017101	0.0022015	-0.090594	0.18672	-0.073150	-0.19465	-0.20130
DHNTCC	0.20636	0.045108	0.011562	-0.049032	0.19417	0.034315	-0.13527	-0.13479
DHTTCCI	0.18013	0.060397	-0.030037	-0.12642	0.048780	-0.045643	-0.23802	-0.24626
TRTNIPC	-0.053356	-0.14151	-0.17049	-0.073052	0.058841	-0.063042	-0.14528	-0.12242
PTCO	0.024932	0.15856	0.23471	0.21840	-0.29848	0.17536	0.25698	0.23684
PECCP	0.15547	0.29755	0.36119 *	0.30913 **	0.10166	0.28122	0.28359	0.25112

Table B.7							
	REMBASE	GANHO	REMHOR	REMTC	GATC	REMHTC	PTCO
HNTCOCI	-0.23464	-0.26561	-0.32572 **	0.0031918	0.087337	-0.12544	-0.43125 *
HNTCOC	-0.79854 *	-0.82949 *	-0.87301 *	-0.26688	0.062986	-0.45170 *	-0.64940 *
HTTCOCI	-0.13411	-0.16040	-0.23446	0.070811	0.081724	-0.032109	-0.35047 **
DHNTCCI	-0.51979 *	-0.53817 *	-0.52640 *	-0.25730	0.091528	-0.73069 *	-0.17288
DHNTCC	-0.50027 *	-0.55722 *	-0.52814 *	-0.18941	0.074149	-0.69222 *	-0.24080
DHTTCCI	-0.41527 *	-0.44990 *	-0.45144 *	-0.13796	0.099098	-0.61592 *	-0.15868
TRTNIPC	-0.44695 *	-0.41459 *	-0.40389 *	-0.24971	0.056565	-0.25668	0.038402
PTCO	0.54899 *	0.63310 *	0.58870 *	0.34288 **	0.30564	0.39891 *	1
PECCP	0.50985 *	0.48157 *	0.51336 *	0.42705 *	-0.26441	0.40777 *	0.49820 *

Table B.8								
	HCI	HCIVAR	HCISIG	HCICV	HC	HCVAR	HCSIG	HCCV
HNTCOCI	0.98859 *	-0.43727 *	-0.28616	-0.54443 *	0.67601 *	-0.087767	-0.014526	-0.12600
HNTCOC	0.64791 *	0.30734 **	0.42693 *	0.21710	0.97695 *	0.15006	0.29020	0.14395
HTTCOCI	0.97269 *	-0.50774 *	-0.37282 *	-0.61071 *	0.61500 *	-0.12879	-0.071164	-0.17564
DHNTCCI	0.22129	0.28004	0.34201 *	0.28049	0.51227 *	0.24973	0.24997	0.19290
DHNTCC	0.30692 **	0.27696	0.36820 *	0.27023	0.57546 *	0.28106	0.31540 **	0.24890
DHTTCCI	0.27916	0.19776	0.25223	0.19669	0.52070 *	0.24893	0.23966	0.17959
TRTNIPC	-0.65988 *	0.80249 *	0.72157 *	0.87729 *	0.065091	0.20309	0.25640	0.25537
PTCO	-0.43156 *	-0.29510	-0.41112 *	-0.21892	-0.63741 *	-0.12007	-0.25401	-0.16639
PECCP	-0.18121	-0.45936 *	-0.50630 *	-0.36170 *	-0.49944 *	-0.20674	-0.26719	-0.18561

Table B.9								
	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
TXDES	0.38283 *	0.24060	0.22825	-0.035607	0.24831	-0.021076	-0.23600	-0.26990
TXDESH	0.43103 *	0.27453	0.25455	-0.033401	0.31477 **	0.00014773	-0.20554	-0.24994
TXDESM	0.22743	0.17734	0.17628	0.054669	0.16495	0.050090	-0.076072	-0.087105
DTCOCI	-0.065370	-0.14734	-0.15078	-0.18822	0.30948 **	-0.22056	0.18088	0.18800
DTCOC	-0.089606	-0.16399	-0.18580	-0.20647	0.24616	-0.23394	0.10242	0.12316
TCEX	0.13092	0.25737	0.18512	0.063564	-0.32702 **	0.065900	0.028868	0.010566
HTCEX	-0.095516	-0.097343	-0.21668	-0.14127	-0.026581	-0.070903	0.014619	0.035672
HEXTPTR	0.10394	0.21037	0.10689	-0.017282	-0.28964	0.021122	0.014558	0.00027459
HEXTPC	0.093183	0.19742	0.095494	-0.022812	-0.29908	0.013496	0.022041	0.0075878

Table B.10

	REMBASE	GANHO	REMHOR	REMTC	GATC	REMHTC	PTCO
TXDES	-0.34851 **	-0.35040 **	-0.40468 *	-0.012591	0.45096 *	-0.22967	-0.16487
TXDESH	-0.16610	-0.20459	-0.25027	0.11556	0.20019	-0.12415	-0.055509
TXDESM	-0.37792 *	-0.33113 **	-0.37865 *	-0.17115	0.63196 *	-0.27947	-0.15452
DTCOCI	-0.29286	-0.38787 *	-0.26885	-0.26966	-0.28447	-0.38883 *	-0.50375 *
DTCOC	-0.38591 *	-0.44393 *	-0.35283 *	-0.46300 *	-0.30890 **	-0.52550 *	-0.46924 *
TCEX	0.54059 *	0.56861 *	0.47586 *	0.35627 *	0.0037521	0.42678 *	0.47292 *
HTCEX	-0.11509	-0.13878	-0.13214	0.045092	0.039659	0.043107	-0.036493
HEXTPTR	0.46129 *	0.47675 *	0.39584 *	0.39555 *	0.025479	0.46722 *	0.37765 *
HEXTPC	0.47791 *	0.49529 *	0.41507 *	0.39427 *	0.026365	0.47119 *	0.39793 *

Table B.11								
	HCI	HCIVAR	HCISIG	HCICV	HC	HCVAR	HCSIG	HCCV
TXDES	0.49030 *	-0.049756	0.067391	-0.032889	0.59381 *	0.12548	0.23943	0.14658
TXDESH	0.42560 *	-0.17459	-0.074805	-0.12473	0.46325 *	-0.032782	0.078115	0.0047211
TXDESM	0.35540 *	0.076669	0.18120	0.072885	0.48064 *	0.27310	0.37062 *	0.29368
DTCOCI	-0.27056	0.56492 *	0.60539 *	0.59700 *	0.092595	0.39490 *	0.42451 *	0.43586 *
DTCOC	-0.33217 **	0.68489 *	0.70203 *	0.69709 *	0.12428	0.39848 *	0.42197 *	0.42478 *
TCEX	0.095544	-0.55430 *	-0.62764 *	-0.55000 *	-0.26987	-0.31473 **	-0.43372 *	-0.41108 *
HTCEX	-0.23093	0.43320 *	0.41408 *	0.43966 *	0.086715	0.27786	0.31167 **	0.30327
HEXTPTR	0.097319	-0.42506 *	-0.47980 *	-0.42155 *	-0.17953	-0.19647	-0.27244	-0.25793
HEXTPC	0.072020	-0.42871 *	-0.48879 *	-0.42306 *	-0.20923	-0.20581	-0.29046	-0.27224

Table B.12

	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
VABTC	-0.060970	-0.041203	-0.026840	0.019937	0.20842	-0.00039286	0.20535	0.21254
PEFTC	0.041597	0.078891	0.078612	0.098358	0.31046 **	0.094189	0.25287	0.24316
PINTC	0.12352	0.14427	0.10140	0.035480	0.35116 *	0.058209	0.29273	0.26383
VABRTC	0.057795	-0.024857	-0.0057568	-0.15532	0.23413	-0.19675	-0.033470	-0.027725
PEFRTC	0.087799	0.13084	0.12682	0.11823	0.29238	0.12210	0.21542	0.20494
PINRTC	0.11030	0.13319	0.082480	0.0093057	0.34744 *	0.034840	0.30796	0.28113
VABPTC	-0.15724	0.020475	0.00098284	0.32305 **	-0.090591	0.37310 *	0.46503 *	0.46447 *
PEFPTC	-0.16487	-0.19237	-0.19128	-0.10569	-0.090529	-0.12202	0.19176	0.19687
PINPTC	0.11049	0.10997	0.13148	0.13008	0.14161	0.12504	0.036419	0.015861
VABT	-0.13796	-0.11121	-0.099576	-0.048111	-0.14819	-0.10348	0.23376	0.24352
VABTE	-0.17046	-0.18787	-0.20736	0.011327	-0.050138	-0.0016265	0.090648	0.13710
VABTTC	-0.093389	-0.059601	-0.068191	0.020590	0.13329	0.018878	0.18879	0.19825
VABTETC	-0.11374	-0.086277	-0.10060	-0.028031	0.087006	-0.028190	0.13120	0.14794
VABRTTC	0.035772	-0.042810	-0.043380	-0.17089	0.16851	-0.19809	-0.069611	-0.062081
VABRTET	0.012652	-0.067068	-0.073019	-0.20594	0.12722	-0.23082	-0.11025	-0.096196
REMVA	0.081031	-0.11658	-0.090831	-0.40699 *	0.035029	-0.47135 *	-0.45970 *	-0.45837 *
REMVA (29)	0.23917	0.28511	0.30373	0.21990	-0.059371	0.24763	-0.076910	-0.11610

Table B.13							
	REMBASE	GANHO	REMHOR	REMTC	GATC	REMHTC	PTCO
VABTC	0.049324	-0.037594	0.0084181	0.19643	0.036901	0.17343	-0.096843
PEFTC	0.058974	-0.056868	0.0079524	0.15113	-0.12301	0.052532	-0.19908
PINTC	0.12668	-0.010923	0.091026	0.17108	-0.38072 *	0.010701	-0.39092 *
VABRTC	-0.18335	-0.25860	-0.25633	-0.026059	-0.028612	-0.12306	-0.15525
PEFRTC	0.012303	-0.089409	-0.041134	0.086865	-0.15115	-0.035306	-0.15028
PINRTC	0.13162	-0.0037994	0.096822	0.12647	-0.39613 *	-0.050055	-0.37145 *
VABPTC	0.41381 *	0.41576 *	0.48438 *	0.27571	0.066213	0.39213 *	0.15589
PEFPTC	0.23610	0.23602	0.27576	0.15626	0.12059	0.27358	-0.011663
PINPTC	0.040460	-0.023561	0.020094	0.28096	-0.10416	0.29414	-0.20470
VABT	0.37849 *	0.43348 *	0.38966 *	-0.27470	-0.21781	0.00071047	0.23005
VABTE	0.070841	0.097402	0.068487	-0.60532 *	-0.44205 *	-0.28477	-0.14970
VABTTC	0.038306	-0.023201	0.0090402	0.14213	0.12455	0.12359	-0.026115
VABTETC	-0.0072794	-0.069512	-0.032286	0.19179	0.14682	0.14515	-0.052086
VABRTTC	-0.20644	-0.25906	-0.27220	-0.082672	0.042705	-0.18013	-0.097364
VABRTET	-0.23775	-0.29156	-0.29855	-0.031419	0.065145	-0.15029	-0.11840
REMVA	-0.30912 **	-0.30969 **	-0.37355 *	-0.11929	0.029216	-0.18602	-0.12395
REMVA (29)	0.15799	0.18926	0.13173	0.38063 *	0.21065	0.21918	0.43177 *

Table B.14								
	HCI	HCIVAR	HCISIG	HCICV	HC	HCVAR	HCSIG	HCCV
VABTC	-0.044043	0.13117	0.14570	0.12717	0.000034341	0.13885	0.15122	0.15086
PEFTC	0.028505	0.037639	0.079612	0.061603	0.021490	0.12794	0.14200	0.14271
PINTC	0.071443	-0.099869	-0.037502	-0.038943	-0.023646	0.10301	0.13029	0.15323
VABRTC	0.12146	0.17586	0.19021	0.13994	0.25537	0.14300	0.13035	0.084148
PEFRTC	0.049614	0.017349	0.056735	0.038974	0.045587	0.055397	0.053809	0.044063
PINRTC	0.029025	-0.054806	0.0031191	0.0050240	-0.042694	0.12897	0.14517	0.17016
VABPTC	-0.30223	-0.13148	-0.13363	-0.067697	-0.48930 *	-0.073020	-0.039890	0.044406
PEFPTC	-0.14522	0.0033893	-0.0084213	0.013866	-0.20613	0.14793	0.19556	0.24790
PINPTC	0.20740	-0.24508	-0.20580	-0.21583	0.064915	-0.085665	-0.027211	-0.025637
VABT	-0.22766	-0.23110	-0.32877	-0.24985	-0.43906 *	-0.32178 **	-0.45831 *	-0.41332 *
VABTE	-0.21472	0.19393	0.11259	0.11681	-0.14395	-0.15989	-0.21418	-0.20298
VABTTC	-0.074663	0.15259	0.16046	0.14499	-0.018143	0.16069	0.16022	0.15975
VABTETC	-0.071624	0.19659	0.20389	0.17859	0.0092048	0.17386	0.17820	0.17426
VABRTTC	0.10782	0.19474	0.20243	0.15315	0.25731	0.16119	0.13548	0.086114
VABRTET	0.10336	0.23282	0.24004	0.18331	0.27138	0.17310	0.15266	0.10197
REMVA	0.27447	0.10951	0.10224	0.045081	0.43081 *	0.11479	0.10271	0.034446
REMVA (29)	0.24031	-0.43233 *	-0.41988	-0.38432 *	0.020407	-0.16419	-0.14243	-0.14826

Table B.15								
	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
EDUC	-0.071478	0.094141	0.065318	0.20392	-0.13920	0.20139	0.69768 *	0.67703 *
EDUC1	-0.066170	0.10011	0.071800	0.20642	-0.13689	0.20312	0.69461 *	0.67333 *
ANTIG	0.0081442	0.23909	0.29089	0.37146 *	-0.21690	0.33428 **	0.35464 *	0.33678 **
IDAD	-0.22865	-0.012915	-0.064248	0.19823	-0.46727 *	0.20464	0.25444	0.27535
PCMQP	0.051200	-0.032446	0.086726	-0.093163	0.25413	-0.15463	0.073787	0.070804
PCEM	-0.033146	-0.12554	-0.065662	-0.11512	0.22993	-0.12481	0.036597	0.053611

Table B.16							
	REMBASE	GANHO	REMHOR	REMTC	GATC	REMHTC	PTCO
EDUC	0.82100 *	0.75136 *	0.83940 *	0.32418 **	-0.026753	0.42251 *	0.23462
EDUC1	0.82279 *	0.75279 *	0.83994 *	0.32858 **	-0.027223	0.42736 *	0.23309
ANTIG	0.64574 *	0.70863 *	0.65595 *	0.11566	-0.12572	0.21975	0.63263 *
IDAD	0.45833 *	0.55158 *	0.50366 *	0.024661	0.12865	0.15326	0.60233 *
PCMQP	-0.29737	-0.36339 *	-0.25119	0.13446	-0.010990	-0.039468	-0.12604
PCEM	-0.27963	-0.35199 **	-0.25072	-0.056680	-0.11202	-0.18432	-0.30082

Table B.17								
	HCI	HCIVAR	HCISIG	HCICV	HC	HCVAR	HCSIG	HCCV
EDUC	-0.22649	-0.38263 *	-0.38983 *	-0.32958 **	-0.69301 *	0.13747	0.067950	0.18359
EDUC1	-0.21809	-0.39205 *	-0.39869 *	-0.33901 **	-0.68992 *	0.13313	0.063553	0.17855
ANTIG	-0.050467	-0.71238 *	-0.78820 *	-0.68510 *	-0.60343 *	-0.43411 *	-0.58660 *	-0.51705 *
IDAD	-0.46082 *	-0.081031	-0.20282	-0.068848	-0.58585 *	-0.079247	-0.21888	-0.14722
PCMQP	-0.36967 *	0.51564 *	0.50437 *	0.57983 *	0.017494	0.38109 *	0.37638 *	0.40325 *
PCEM	-0.28391	0.56968 *	0.56849 *	0.58224 *	0.084495	0.43845 *	0.43746 *	0.45349 *

Table B.18								
	G94T	NT94T	ND94T	HGRPT	HGRS	TGRPT	TSIND	TSIND1
DIMEMP	-0.10819	0.21081	0.44694 *	0.49950 *	-0.021152	0.26641	0.22854	0.22604
DIMEST	-0.017215	0.12392	0.27249	0.24482	-0.18668	0.13078	-0.055572	-0.080064
ESTEMP	-0.14997	0.11235	0.28641	0.35583 *	-0.11101	0.17603	0.33288 **	0.33052 **
IG	-0.0016088	0.19437	0.25029	0.24812	-0.28017	0.18461	0.40734 *	0.38027 *
HI	-0.19091	-0.12393	-0.10551	-0.055300	-0.35091 **	-0.096527	-0.12068	-0.13275
PCTR9	-0.12954	-0.24194	-0.32222 **	-0.21177	0.20361	-0.16964	-0.21815	-0.17528
PCTR200	-0.037516	0.14631	0.19327	0.20541	-0.29585	0.14552	0.36106 *	0.33438 **
PCTR500	-0.059513	0.14920	0.19774	0.21512	-0.25522	0.13637	0.45236 *	0.43811 *

Table B.19							
	REMBASE	GANHO	REMHOR	REMTC	GATC	REMHTC	PTCO
DIMEMP	0.36758 *	0.43122 *	0.36094 *	0.056036	-0.018050	0.29949	0.39327 *
DIMEST	0.33247 **	0.41456 *	0.31806 **	0.27502	0.12299	0.29588	0.70238 *
ESTEMP	0.49787 *	0.57726 *	0.52215 *	0.014706	-0.057753	0.36224 *	0.44090 *
IG	0.70955 *	0.78648 *	0.73944 *	0.31736 **	0.073504	0.45898 *	0.84995 *
HI	0.31645 **	0.39108 *	0.31336 **	0.23312	0.058404	0.22898	0.45815 *
PCTR9	-0.52263 *	-0.58434 *	-0.54288 *	-0.42458 *	-0.35312 **	-0.40496 *	-0.93854 *
PCTR200	0.69003 *	0.76951 *	0.71757 *	0.29237	0.029022	0.42495 *	0.80219 *
PCTR500	0.70584 *	0.77028 *	0.73164 *	0.31594 **	0.033935	0.56793 *	0.64940 *

Table B.20								
	HCI	HCIVAR	HCISIG	HCICV	HC	HCVAR	HCSIG	HCCV
DIMEMP	-0.15788	-0.32759 **	-0.43106 *	-0.32317 **	-0.37446 *	-0.33560 **	-0.42196 *	-0.38186 *
DIMEST	-0.13555	-0.43514 *	-0.56848 *	-0.39641 *	-0.32376 **	-0.44438 *	-0.57665 *	-0.54268 *
ESTEMP	-0.30564	-0.36735 *	-0.48132 *	-0.34812 *	-0.59419 *	-0.36755 *	-0.46497 *	-0.39755 *
IG	-0.47152 *	-0.47741 *	-0.61442 *	-0.37639 *	-0.77889 *	-0.37587 *	-0.51460 *	-0.41085 *
HI	-0.047443	-0.43600 *	-0.56168 *	-0.44556 *	-0.29738	-0.48227 *	-0.66537 *	-0.63428 *
PCTR9	0.26474	0.43630 *	0.50687 *	0.33053 **	0.52608 *	0.13276	0.23436	0.16390
PCTR200	-0.46258 *	-0.48424 *	-0.62942 *	-0.38888 *	-0.76543 *	-0.42215 *	-0.56732 *	-0.46596 *
PCTR500	-0.45294 *	-0.42038 *	-0.55069 *	-0.34201 **	-0.74409 *	-0.38668 *	-0.49683 *	-0.39921 *

Table B.21								
	G93T	NT93T	ND93T	HGRPT93	HGRS93	TGRPT93	TSIND	TSIND1
HNAOT93	0.34165 **	0.31206 **	0.33416 **	0.42068 *	0.22761	0.38189 *	-0.43681 *	-0.45070 *
ANAAT93	-0.12149	-0.073377	-0.079040	0.032186	0.12998	0.013477	-0.60389 *	-0.60110 *
ANADN93	0.26349	0.21917	0.22880	0.45235 *	0.14640	0.39418 *	-0.34433 **	-0.36853 *
ANADP93	0.091756	-0.081495	-0.075841	-0.15969	0.0066747	-0.13585	-0.12152	-0.13107
ANASD93	0.17779	0.41487 *	0.37290 *	0.26064	-0.049438	0.24161	0.61456 *	0.59573 *
ANAAI93	0.46543 *	0.28196	0.33249 **	0.26843	0.15159	0.27545	0.26207	0.23680
ANAMP93	0.41156 *	0.11556	0.18143	-0.070243	0.19432	-0.017300	0.091201	0.070093
ANAOC93	0.38132 *	0.45284 *	0.47508 *	0.33038 **	0.18191	0.32157 **	-0.16953	-0.15806

Table B.22						
	REMBA93	GANHO93	REMHO93	REMTC93	GATC93	REMHTC93
HNAOT93	-0.13839	-0.077866	-0.22442	-0.036275	0.15466	0.12285
ANAAT93	-0.14607	-0.071734	-0.20398	0.10818	0.14239	0.33123 **
ANADN93	0.0082802	0.065081	-0.051205	-0.062420	0.16807	0.044948
ANADP93	-0.27336	-0.34250 **	-0.22028	0.0047848	0.059031	0.013905
ANASD93	0.38856 *	0.38970 *	0.37867 *	-0.17678	-0.098750	-0.29725
ANAAI93	0.053108	0.027566	0.043260	-0.27534	-0.080354	-0.25303
ANAMP93	-0.24546	-0.33447 *	-0.22541	-0.26778	-0.086594	-0.18051
ANAOC93	-0.19543	-0.15666	-0.28615	0.038366	0.052687	0.074294

Table B.23							
	EDUC93	ANTIG93	IDAD93	PCMQP93	HNTCCI93	HNTCC93	HTTCCI93
HNAOT93	-0.44545 *	0.34744 **	-0.037900	-0.30649 **	0.45604 *	0.34788 **	0.46972 *
ANAAT93	-0.45050 *	-0.083521	-0.12874	-0.51048 *	0.22688	0.31550 **	0.22577
ANADN93	-0.28773	0.42880 *	0.079984	-0.21911	0.27729	0.10914	0.29945
ANADP93	-0.086163	-0.33320 **	-0.17530	0.57781 *	-0.37480 *	-0.054982	-0.42136 *
ANASD93	0.44360 *	0.47352 *	0.19052	0.11965	0.010528	-0.21634	0.057175
ANAAI93	0.068452	0.37987 *	-0.089104	0.10993	0.22490	-0.076373	0.23183
ANAMP93	-0.025228	-0.10806	-0.42103 *	0.50143 *	0.0679803	0.068103	0.0090031
ANAOC93	-0.34871 **	0.26767	0.010329	-0.22539	0.54124 *	0.49072 *	0.55915 *

Table B.24

	HCI93	HCIVAR93	HCISIG93	HCICV93	HC93	HCVAR93	HCSIG93	HCCV93
HNAOT93	0.49305 *	-0.33366 **	-0.34253 **	-0.38240 *	0.45449 *	-0.4002 *	-0.40623 *	-0.46041 *
ANAAT93	0.26267	-0.029219	-0.046340	-0.10542	0.33636 **	-0.29985	-0.24611	-0.28333
ANADN93	0.33800 **	-0.33657 **	-0.37359 *	-0.35218 **	0.27400	-0.32890 **	-0.42614 *	-0.45243 *
ANADP93	-0.36191 *	0.47285 *	0.46438 *	0.51572 *	-0.029420	0.56987 *	0.53686 *	0.50894 *
ANASD93	-0.029139	-0.26623	-0.26015	-0.19546	-0.27220	0.20713	0.26945	0.29143
ANAAI93	0.22468	-0.37553 *	-0.34906 **	-0.33539 **	0.0086814	-0.10825	-0.11146	-0.11094
ANAMP93	0.043183	0.015297	0.065265	0.056680	0.076140	0.23289	0.30982 **	0.28202
ANAOC93	0.51672 *	-0.27845	-0.24410	-0.34169 **	0.46884 *	-0.36293 *	-0.28275	-0.34456 **

Table B.25

	DIMEMP93	DIMEST93	IG93	HI93	PCTR993	PCT20093	PCT50093	PTCO93
HNAOT93	0.20724	0.41868 *	0.15361	0.28590	-0.35913 **	0.13457	0.083399	0.27120
ANAAT93	-0.055377	0.47908 *	-0.0041335	0.37066 *	-0.071265	0.011730	-0.0072142	0.10729
ANADN93	0.25070	0.46820 *	0.31727 **	0.45584 *	-0.46154 *	0.30378	0.25954	0.40260 *
ANADP93	-0.23492	-0.22210	-0.23747	-0.31752 **	0.15140	-0.23766	-0.27676	-0.13857
ANASD93	0.45695 *	0.065042	0.37317 *	-0.11380	-0.25710	0.36380 *	0.36850 *	0.22434
ANAAI93	0.038454	-0.068994	0.13031	-0.13027	-0.35171 **	0.088503	0.027302	0.19515
ANAMP93	-0.32260 **	-0.33124 **	-0.30478	-0.51970 *	0.051295	-0.32850 **	-0.40233 *	-0.22150
ANAOC93	0.27408	0.059377	-0.042250	-0.11336	-0.096799	-0.070483	-0.085497	0.00068295

Appendix 3: Choice of the Dependent Variable: A Representative Agent Test

It is the purpose of this appendix to justify the choice of the dependent variables. Given the data sources, we can choose to model either:

- aggregate strikes, choosing for dependent variables G94T, NT94T and ND94T

- strikes per individual employed, explaining TGRPT ≈ NT94T / TCOCI and HGRPT ≈ ND94T / TCOCI. This approach has a twofold argument for it: on the one hand, it in the line of our theoretical section, the individual decision and loss per strike is at stake. On the other, most of the constructed variables are individual, per worker, indicators.

- (sector) strikes per firm in the sector, explaining GREMP ≈ G94T / EMPT, TGRPE ≈ NT94T / EMPT and HGRPE ≈ ND94T / EMPT. This approach would also be reasonable: bargaining models confront two parties, the union and the employer; the latter can be reasonably be associated to a firm. Important variables for bargaining studies refer to the firm as the unit, namely, industry concentration, firm size.

In 1994, 296 strikes were recorded (excluding Public Administration), involving 71129 workers and 78743 workdays loss. Only 31 (10,5%) strikes were multi-firm, involving 21622 (30,4%) workers and a loss of 15148 (19,2%) workdays; however, apparently un-synchronized firm strikes may reflect a more aggregate bargaining strategy. Total employment, not self-employed, recorded in TCOCI was 1844008 (1960906 in some of the official Tables) workers, and 176882 firms were covered (data excludes Public Administration).

A first step was to apply stepwise regression to three formulations. The final versions achieved with an entering significance level of 20% and exit at 25% are presented below.

We did not consider number of strikes per worker employed in the sector. We add the results of the regression on HGRS, strike mean duration, so that the reader can appreciate why we discarded its study at this stage.

Table C.1 – Aggregate Indexes			
Independent Variables	G94T	NT94T	ND94T
CONSTANT	-312.595 (62.897) [0.000]	-56558.933 (9570.321) [0.000]	-52727.256 (11749.084) [0.000]
TCOCI	0.0001365 (0.000) [0.000]	0.02404 (0.005) [0.000]	0.02449 (0.006) [0.000]
TXDES	3.813 (0.884) [0.000]	632.002 (144.278) [0.000]	576.995 (164.464) [0.002]
TCEX	1.417 (0.299) [0.000]	261.570 (47.256) [0.000]	151.590 (54.416) [0.011]
DTCOCI		-95.171 (49.146) [0.068]	
PECCP	2.462 (0.616) [0.001]	426.247 (94.995) [0.000]	479.317 (110.781) [0.000]
TSIND	0.221 (0.082) [0.014]	67.852 (13.921) [0.000]	51.494 (20.079) [0.018]
DIMEMP		6.257 (1.474) [0.000]	9.542 (1.755) [0.000]
HCISIG	6.050 (1.457) [0.000]	1312.790 (252.696) [0.000]	718.855 (279.204) [0.018]
DPCMQP	10.887 (2.146) [0.000]	2101.052 (346.495) [0.000]	1470.217 (402.662) [0.002]
DIDADE	3.062 (1.642) [0.076]		
GATC		-81.223 (51.854) [0.134]	
EDUC			-436.693 (343.773) [0.219]
SSE	2409.896	51316213	76020518
RBAR2	0.714	0.819	0.743
F-TEST	10.069 [0.000]	14.083 [0.000]	10.302 [0.000]

Table C.2 – (Per) Firm Indexes			
Independent Variables	GREMP	TGRPE	HGRPE
CONSTANT	0.01434 (0.003) [0.000]	7.892 (2.894) [0.012]	90.931 (36.580) [0.021]
DIMEMP	0.00008453 (0.000) [0.000]	0.223 (0.006) [0.000]	3.145 (0.072) [0.000]
IG		-26.074 (5.460) [0.000]	-418.119 (83.690) [0.002]
DTCOC	-0.0005035 (0.000) [0.000]		
TRTNIPC	0.0005387 (0.000) [0.002]		
TCEX			2.840 (2.012) [0.172]
DEDUC		13.187 (5.303) [0.021]	278.760 (77.066) [0.102]
DIDADE		-8.733 (1.034) [0.000]	-99.827 (12.907) [0.000]
DANTIG	-0.001139 (0.002) [0.000]		
DHNTCC	0.005113 (0.001) [0.000]	6.060 (1.335) [0.000]	
DHNTCCI			95.925 (16.153) [0.000]
DHCISIG		-4.263 (1.792) [0.026]	
GATC	-0.0007622 (0.000) [0.000]		
SSE	7.036E-04	738.668	120949.36
RBAR2	0.926	0.987	0.989
F-TEST	61.396 [0.000]	356.986 [0.000]	417.321 [0.000]

Table C.3 – (Per) Worker Indexes			
Independent Variables	TGRPT	HGRPT	HGRS
CONSTANT	0.166 (0.040) [0.000]	0.512 (0.404) [0.218]	62.885 (19.103) [0.003]
DIMEMP	0.0001194 (0.000) [0.020]	0.001290 (0.000) [0.017]	
TSIND	0.001184 (0.000) [0.013]		
DTCOCI	-0.004821 (0.001) [0.001]		
DIDADE		-0.304 (0.100) [0.006]	
DANTIG	-0.141 (0.027) [0.000]	-0.639 (0.251) [0.018]	
DHNTCCI	0.03842 (0.010) [0.001]		
GATC	-0.009084 (0.002) [0.000]	-0.03703 (0.017) [0.044]	
TCOCI	-3.331E-07 (0.000) [0.063]	-2.374E-06 (0.000) [0.171]	
ANTIG		0.09048 (0.035) [0.017]	
IDAD			-1.410 (0.504) [0.009]
SSE	6.725E-02	6.849	1943.872
RBAR2	0.663	0.544	0.190
F-TEST	9.140 [0.000]	5.938 [0.001]	7.821 [0.009]

One of the distinctive features of the results is the systematic significance of firm size – DIMEMP, and the importance of variables in changes rather than in levels. The latter occurs with traditional human capital proxys and with wages.

The best fits were obtained for regressions where the dependent variable was defined in per firm in the sector – Table C.2. -, followed by aggregate formulations. Also, TCOCI does not show up in the regressions in individual indexes – yet they do in aggregates -, suggesting that these (in TGRPT and HGRPT) and aggregate formulations may be interchangeable. To evaluate the relative performance of each regression we performed some basic comparisons, carried out and explained below.

2. We considered two-by-two encompassing tests between:
- number of strikes and number of strikers and total days lost in strike.
- aggregate and firm indexes for number of strikes.
- aggregate and individual indexes for workers on strike and lost hours/days.
- firm and individual indexes for workers on strike and lost hours/days.

The test can be explained as follows:

Let

$$(C.1) \qquad Y_i = F(X_i) + \varepsilon_i$$

represent the aggregate formulation and

$$(C.2) \qquad y_i = G(x_i) + \eta_i$$

the unit formulation, such that $y_i = Y_i / T_i$.

. Assume $Var(\varepsilon_i) = K\, T_i^2$. Then (C.1) should be estimated in the form:

$$(C.1') \qquad y_i = F(X_i)/T_i + \varepsilon_i/T_i$$

We can estimate

$$(C.3) \qquad y_i = F(X_i)/T_i + G(x_i) + \eta_i$$

and confront it both with (C.1´); and with (C.2). If we do not reject the first null – H_0: $G(x_i) = 0$ - but reject the second – H_0: $F(X_i)/T_i = 0$, we choose (C.1), the more aggregate version of the two. If the opposite occurs, we choose (C.2).

. Assume now that $Var(\eta_i) = R / T_i^2$. Then (C.2) should be estimated as:

$$(C.2') \qquad Y_i = G(x_i)\, T_i + \eta_i\, T_i$$

We can estimate

$$(C.4) \qquad Y_i = F(X_i) + G(x_i) * T_i + \varepsilon_i$$

and confront it with (C.1); and with (C.2´). If we do not reject the first null – H_0: $G(x_i) * T_i = 0$ - but reject the second – H_0: $F(X_i) = 0$, we prefer (C.1), the more aggregate version of the two. If the opposite occurs, we choose (C.2´).

Case 1: Y_i = NT94T_i; T_i = NT94T_i/G94T_i ; y_i = G94T_i.

(In cases 1 and 2, T_i was set to 0 when G94T (NT94T and ND94T) was 0; its inverse was set to missing for those observations.)

Table D.1

Regressand	G94T	H_0: $F(X_i) / T_i = 0$ 1.138 [0.430]	H_0: $G(x_i) = 0$ 2.153 [0.134]
	NT94T	H_0: $G(x_i) * T_i = 0$ 1.100 [0.439]	H_0: $F(X_i) = 0$ 0.964 [0.527]

The first line would mildly suggest the model in disruptions rather than in individuals – but that conclusion is only valid at a 14% significance level. The second line indicates definite non-rejection of both nulls and interchangeability of both formulations or sets of covariates.

Case 2: Y_i = ND94T_i; T_i = ND94T_i/G94T_i ; y_i = G94T_i.

Table D.2

Regressand	G94T	H_0: $F(X_i) / T_i = 0$ 1.133 [0.424]	H_0: $G(x_i) = 0$ 0.679 [0.714]
	ND94T	H_0: $G(x_i) * T_i = 0$ 1.418 [0.288]	H_0: $F(X_i) = 0$ 0.854 [0.595]

The tests always lead to a non-rejection of the null – and rejection of the restricted best version, in the presence of the other, appropriately scaled, so to speak, regressors.

Case 3: Y_i = G94T$_i$; T_i = EMPT$_i$; y_i = GREMP$_i$.

Table D.3			
Regressand	GREMP	H_0: $F(X_i) / T_i = 0$ 3.323 [0.0219]	H_0: $G(x_i) = 0$ 4.410 [0.00882]
	G94T	H_0: $G(x_i) * T_i = 0$ 1.559 [0.227]	H_0: $F(X_i) = 0$ 4.838 [0.00445]

Both formulations seem incomplete from the first regression. The second line of the table suggests the aggregate would be preferable.

Case 4: Y_i = NT94T$_i$; T_i = TCOCI$_i$; y_i = TGRPT$_i$.

Table D.4			
Regressand	TGRPT	H_0: $F(X_i) / T_i = 0$ 3.794 [0.0162]	H_0: $G(x_i) = 0$ 0.616 [0.734]
	NT94T	H_0: $G(x_i) * T_i = 0$ 0.637 [0.718]	H_0: $F(X_i) = 0$ 1.484 [0.255]

The first line/regression suggests the aggregate regression. The second line accepts both (i.e., never rejects the null), but indicates preference for the aggregate (p-value of the test is much lower).

Case 5: Y_i = ND94T$_i$; T_i = TCOCI$_i$; y_i = HGRPT$_i$.

Table D.5			
Regressand	HGRPT	H_0: $F(X_i) / T_i = 0$ 0.897 [0.552]	H_0: $G(x_i) = 0$ 1.452 [0.264]
	ND94T	H_0: $G(x_i) * T_i = 0$ 0.729 [0.634]	H_0: $F(X_i) = 0$ 2.900 [0.0364]

The aggregate regression seems preferable in the second regression. The regression in HGRPT accepts both.

Case 6: Y_i = $TGRPE_i$; T_i = $TCOCI_i/EMPT_i$; y_i = $TGRPT_i$.

Table D.6			
Regressand	TGRPT	H_0: $F(X_i) / T_i = 0$ 0.227 [0.973]	H_0: $G(x_i) = 0$ 6.985 [0.00067]
	TGRPE	H_0: $G(x_i) * T_i = 0$ 31.448 [0.000]	H_0: $F(X_i) = 0$ 0.250 [0.964]

Consistently, the regression on TGRPT is better than on TGRPE.

Case 7: Y_i = $HGRPE_i$; T_i = $TCOCI_i/EMPT_i$; y_i = $HGRPT_i$.

Table D.7			
Regressand	HGRPT	H_0: $F(X_i) / T_i = 0$ 0.639 [0.698]	H_0: $G(x_i) = 0$ 6.062 [0.00140]
	HGRPE	H_0: $G(x_i) * T_i = 0$ 74.774 [0.000]	H_0: $F(X_i) = 0$ 3.940 [0.0110]

From the first line, the regression on HGRPT is better than on HGRPE. From the second, however, both are rejected.

3. Finally, we present some Glesjer-type tests for the five variables of interest. In particular, we were interested in evaluating the weighting of types (C.2) by the square of T_i ($TCOCI_i^2$ for regressions on TGRPT and HGRPT; $EMPT_i^2$ for regressions on GREMP, TGRPE and HGRPE); and by T_i, considering the departure from a model in individuals but for which we only have mean data for each group i, i.e., averages over T_i individuals.

Table E.1

	SQRES		ABSRES	
	NT94T2 / G94T2	NT94T / G94T	NT94T / G94T	SRT(NT94T / G94T)
NT94T	-0.924 [0.363]	-0.698 [0.491]	-0.924 [0.364]	-0.314 [0.756]
	ND94T2 / G94T2	ND94T / G94T	ND94T / G94T	SRT(ND94T / G94T)
ND94T	-0.388 [0.701]	-0.0177 [0.986]	0.138 [0.891]	0.822 [0.418]
	G94T2 / NT94T2	G94T / NT94T	G94T / NT94T	SRT(G94T / NT94T)
G94T	-0.357 [0.725]	-0.386 [0.704]	-0.202 [0.842]	-0.204 [0.841]
	G94T2 / ND94T2	G94T / ND94T	G94T / ND94T	SRT(G94T / ND94T)
G94T	-0.340 [0.737]	-0.230 [0.820]	-0.188 [0.853]	-0.0933 [0.927]

Table E.2

	SQRES		ABSRES	
	EMPT2	EMPT	EMPT	SRTEMPT
G94T	0.231 [0.819]	0.573 [0.571]	0.466 [0.645]	0.844 [0.406]
NT94T	-0.776 [0.444]	-0.528 [0.602]	-0.770 [0.448]	-0.242 [0.811]
ND94T	0.0346 [0.973]	-0.167 [0.869]	-0.219 [0.828]	-0.195 [0.847]
	1/EMPT2	1/EMPT	1/EMPT	1/SRTEMPT
GREMP	0.0301 [0.976]	0.0658 [0.948]	-0.0253 [0.980]	-0.0119 [0.991]
TGRPE	-0.741 [0.465]	-0.855 [0.400]	-0.903 [0.374]	-0.880 [0.386]
HGRPE	-0.573 [0.571]	-0.657 [0.516]	-0.712 [0.483]	-0.624 [0.537]

Table E.3

	SQRES		ABSRES	
	TCOCI2	TCOCI	TCOCI	SRTCOCI
NT94T	-0.330 [0.744]	0.102 [0.920]	-0.104 [0.918]	0.316 [0.754]
ND94T	-0.215 [0.831]	-0.179 [0.859]	-0.0571 [0.955]	0.208 [0.837]
	1/TCOCI2	1/TCOCI	1/TCOCI	1/SRTCOCI
TGRPT	-1.033 [0.310]	-1.216 [0.234]	-1.949 [0.061]	-1.9664 [0.059]
HGRPT	-0.445 [0.659]	-0.295 [0.770]	0.224 [0.824]	0.580 [0.566]

Table E.4

	SQRES		ABSRES	
	TCOCI2 / EMPT2	TCOCI / EMPT	TCOCI / EMPT	SRT(TCOCI / EMPT)
TGRPE	-0.423 [0.676]	-0.262 [0.795]	-0.228 [0.822]	0.0229 [0.982]
HGRPE	-0.353 [0.726]	-0.199 [0.844]	-0.297 [0.769]	-0.0591 [0.953]
	EMPT2 / TCOCI2	EMPT / TCOCI	EMPT / TCOCI	SRT(EMPT / TCOCI)
TGRPT	-1.324 [0.196]	-1.317 [0.199]	-1.454 [0.157]	-0.936 [0.357]
HGRPT	-1.656 [0.109]	-1.938 [0.063]	-2.018 [0.053]	-1.866 [0.073]

The statistics suggest weighting the regression of TGRPT by TCOCI2 – which would justify the comparison (with NT94T) of the second type in Case 2 - or (with a slightly lower p-value for the regressions on the inverse of the corresponding absolute errors), preferably, by TCOCI.

HGRPT could eventually be weighted by TCOCI/EMPT or its square - justifying the comparisons (with HGRPE) of the second type in Case 7.

However, at 5%, p-values denote insignificance.

4. When we weighted the stepwise regressions by TCOCI, the included variables changed somewhat but not much. The regressors included in the main text are the result of these weighted regressions, after excluding earnings explanatory variables and performing some basic significance tests.

Appendix 4: Limited Dependent Variables with Mean Data – Alternative Specifications

We provide in this section the formulations for models (32), (34) and (35) that – under $\sigma_\nu = 1$ - would originate the same predictors for both sub-samples. (However, the zero observations counterparts presented in the main text were statistically justified under an index function interpretation of the role of the error tem.)

$$\text{(A.32)} \qquad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\beta' X_i / \sigma_\nu) +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)] / \sigma_\nu\}$$

$$\text{(A.34)} \qquad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\beta'\sqrt{n_i}\ X_i / \sigma_\nu) +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)] / \sigma_\nu\}$$

$$\text{(A.35)} \qquad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi[-\beta'(X_i / \sqrt{n_i}\,) / \sigma_\nu] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\ n_i\ \Phi^{-1}(1\text{-TGRPT}_i) + \beta'\sqrt{n_i}\sqrt{\frac{f_i^2}{F_i(1-F_i)}}\, X_i)] / \sigma_\nu\}$$

Computations are depicted in Table F. The aggregates are usually better (smaller) for models (32) and (35) than for the corresponding version of Table F, (A.32) and (A.35). Comparisons reverse for version (34), which, in any case, is worse than the other two.

Table F

SUMS	Equation		
	(A.32)	(A.34)	(A.35)
SSFI	9321.75441	9744.94384	4138.27882
SSFI1	1.47281D+8	1.40770D+8	1.34798D+8
SSFI2	7.20608D+12	6.83968D+12	7.03551D+12
ABSFI	263.25071	276.65742	169.09582
ABSFI1	25154.74734	27864.51404	24310.21121
ABSFI2	4384940.91589	5351607.23947	4805397.60925
SST	0.13080	0.77645	0.092302
SST1	818.04288	3208.41550	1490.91063
SST2	3.14155D+7	1.72002D+8	4.97000D+7
ABST	0.88214	2.47079	0.83052
ABST1	88.71662	217.49734	123.95590
ABST2	16131.82956	41914.69542	24427.44139
ABST3	2121.01207	11389.01734	5645.31205

Appendix 5: Non-linear Minimum Chi-Square Estimators

We present below the estimates of the absolute fit measures proposed in the text for versions of the models (32) – (42) reformulating the non-zero observations. F_i was previously calculated as in the corresponding linear (inverse normal) version, presented in the text.

$$\text{(B.32)} \qquad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\beta' \sqrt{n_i}\, X_i / \sigma_\nu) + $$
$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i)] / \sigma_\nu\}$$

$$\text{(B.34)} \qquad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\beta'\, n_i\, X_i / \sigma_\nu) + $$
$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' \sqrt{n_i}\, X_i)] / \sigma_\nu\}$$

$$\text{(B.35)} \qquad \text{Log L} = \sum_{i=1}^{30} [(1\text{-TGRPT1}_i) \log\Phi(-\beta'\, X_i / \sigma_\nu) + $$
$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i / \sqrt{n_i}\,)] / \sigma_\nu\}$$

$$\text{(B.37)} \qquad \text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\Phi[-\sqrt{n_i}\ \Phi(\beta' X_i) / \sigma_\nu] + $$
$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i)] / \sigma_\nu\}$$

$$\text{(B.38)} \qquad \text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\Phi[-\sqrt{n_i}\ \Phi(\beta' X_i \sqrt{n_i}\,) / \sigma_\nu] + $$
$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' \sqrt{n_i}\, X_i)] / \sigma_\nu\}$$

Finally, with the third interpretation:

(B.39) $$\text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\Phi[-\sqrt{n_i}\ \Phi(\beta' X_i/\sqrt{n_i}) / \sigma_\nu] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i/\sqrt{n_i})] / \sigma_\nu\}$$

(σ_ν was fixed to 1.)

(B.40) $$\text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\phi[-\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i)] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i)] / \sigma_\nu\}$$

(B.41) $$\text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\phi[-\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i \sqrt{n_i})] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' \sqrt{n_i}\ X_i)] / \sigma_\nu\}$$

(B.42) $$\text{Log L} = \sum_{i=1}^{30} \{(1\text{-TGRPT1}_i) \log\phi[-\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i/\sqrt{n_i})] +$$

$$+ \text{TGRPT1}_i \log\phi\{[\sqrt{\frac{n_i}{F_i(1-F_i)}}\ \text{TGRPT}_i - \sqrt{\frac{n_i}{F_i(1-F_i)}}\ \Phi(\beta' X_i/\sqrt{n_i})] / \sigma_\nu\}$$

Table G

SUMS	Equation (B.32)	(B.34)	(B.35)
SSFI	34.84890 (558.29897) [16.41538]	72.17248 (83.32929) [13.94575]	1.12219D+10 (2.52044D+9) [2.52044D+9]
SSFI1	503724.66766 # (3.01154D+7) [284944.74600]	1478885.65013 (1571493.56932) [807835.32664]	5.40477D+13 (4.13890D+13) [4.13889D+13]
SSFI2	3.53434D+10 # (1.85579D+12) [2.55149D+10 ###]	1.32495D+11 (1.34251D+11) [1.07796D+11]	3.11142D+18 (2.87671D+18) [2.87671D+18]
ABSFI	20.38842 (52.22192) [10.3000]	33.24429 (35.04452) [13.38888]	385346.71851 (179915.55438) [179836.76733]
ABSFI1	2805.94328 # (9475.95327) [1883.87089]	4942.9544 (5069.85871) [3251.49028]	3.97945D+7 (3.06145D+7) [3.0607D+7]
ABSFI2	668050.47876 # (2195742.02097) [514599.98178 ###]	1261881.79877 (1275044.30597) [1001792.10468]	8.27646D+9 (7.38631D+9) [7.38497D+9]
SST	0.15095 (0.17320)	0.89362 (1.29581)	0.34477 (0.34477)
SST1	915.51808 (917.19402)	5035.39856 (7502.43597)	8659.81935 (8659.81935)
SST2	6.54967D+7 (6.54546D+7)	1.99174D+8 (2.46873D+8)	5.62363D+8 (5.62363D+8)
ABST	0.98159 (1.05156)	3.10602 (3.73162)	1.56809 (1.56809)
ABST1	100.38008 (100.22960)	290.84072 (334.35712)	271.37001 (271.37001)
ABST2	21715.12910 (21450.82019)	52213.01631 (56865.22561)	62612.99989 (62612.99989)
ABST3	2747.38631 (3011.69521)	(-)10062.32345 ((-)14714.53276)	62612.99989 (62612.99989)

Table G (Cont.)

SUMS	Equation (B.37)	(B.38)	(B.39)
SSFI	45.93044 (775.72003) [23.28323]	72.29089 (3097.72299) [13.98003]	3134.04543 (490.20350) [100.96364]
SSFI1	527673.03595 (3271681.02646) [394605.67783]	1479047.18198 (5.85075D+7) [803777.93508]	4476333.53302 (2.24582D+7) [1134868.77130]
SSFI2	3.81435D+10 (1.37824D+11) [3.30567D+10]	1.3137D+11 (1.80645D+12) [1.06351D+11]	1.3342D+11 (1.46223D+12) [9.70302D+10]
ABSFI	22.02706 (63.2764) [11.58353]	33.29638 (140.54093) [13.42155]	132.09176 (66.01746) [27.25379]
ABSFI1	2926.89649 (5717.41902) [2143.69346]	4945.51702 (15872.985) [3249.3869]	8211.42971 (10260.29009) [4201.88162]
ABSFI2	707949.16586 (1102415.99417) [592006.00418]	1259433.79077 (2902009.44336) [998046.91779]	1360030.84814 (2381811.89111) [1039091.62598]
SST	0.46136 (3.62135)	0.89669 (6.97907)	0.23790 (2.74255)
SST1	1228.38690 (37146.08892)	5072.91645 (102408.62883)	5358.31600 (82114.18648)
SST2	6.03215D+7 (1.6744D+9)	1.97250D+8 (4.78176D+9)	3.16768D+8 (4.85954D+9)
ABST	1.30690 (5.29650)	3.12014 (8.06934)	1.51899 (5.47380)
ABST1	107.01230 (476.58596)	292.72190 (821.22952)	262.48472 (704.59376)
ABST2	21097.79203 (83142.28695)	52398.66431 (147201.26062)	61057.94987 (145833.23505)
ABST3	3344.55736 ((-)58699.93756)	(-)11008.38233 ((-)105810.97864)	(-)39962.75448 ((-)124738.03967)

Table G (Cont.)			
	Equation		
SUMS	(B.40)	(B.41)	(B.42)
SSFI	29.30667 # [14.65530]	71.83536 [13.85381 ###]	3214.50899 [108.43475]
SSFI1	514947.96122 [282116.08985 ###]	1480201.36216 [820837.13584]	4442564.98694 [1117432.4884]
SSFI2	3.79269D+10 [2.71112D+10]	1.36233D+11 [1.12228D+11]	1.21706D+11 [9.02638D+10]
ABSFI	19.55190 # [10.11584 ###]	33.17107 [13.37414]	132.955 [26.64300]
ABSFI1	2807.50451 [1880.91134 ###]	4951.64781 [3273.09328]	8000.10121 [4005.94505]
ABSFI2	676299.74216 [517387.91379]	1272948.9696 [1015971.50708]	1286677.56384 [980967.33386]
SST	0.078451 #	0.88632	0.11456
SST1	723.00306 #	4998.82094	2714.27077
SST2	3.70468D+7 #	2.09639D+8	1.80640D+8
ABST	0.73866 #	3.08447	1.05927
ABST1	88.06259 #	289.23682	188.37332
ABST2	18846.78509 #	52466.64259	45835.93626
ABST3	904.87532 #	(-)7768.21130	(-)23941.05254

(Estimates of version (B.35) seem very bad.) In general, the measures of the corresponding aggregates from the linearised versions are better than those of Table G – with the exception of models (38) and (41), worse than (B.38) and (B.41) respectively – if we rely on direct cumulative df indicators. (32) and (37) present, usually, also lower measures based on inverse normal than (B.32) and (B.37) respectively.

Of course, F_i could be parameterised as well in the likelihood functions.

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