Innovation and Top Income Inequality*

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Abstract

In this paper we use cross-state panel data to show that top income inequality is (at least partly) driven by innovation. We first establish a positive and significant correlation between various measures of innovativeness and top income inequality in cross-state panel regressions. Two distinct instrumentation strategies suggest that this correlation (partly) reflects a causality from innovativeness to top income inequality, and the effect is significant: for example, when measured by the number of patent per capita, innovativeness accounts on average across US states for around 17% of the total increase in the top 1% income share between 1975 and 2010. Finally, we show that innovation does not increase broader measures of inequality which do not focus on top incomes, and that innovation is positively correlated with social mobility, but less so in states with more intense lobbying activities.

JEL classification: O30, O31, O33, O34, O40, O43, O47, D63, J14, J15

Keywords: top income, inequality, innovation, patenting, citations, social mobility, incumbents, entrant.

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1 Introduction

That the past decades have witnessed a sharp increase in top income inequality worldwide and particularly in developed countries, is by now a widely acknowledged fact.[1] However no consensus has been reached as to the main underlying factors behind this surge in top income inequality. In this paper we argue that, in a developed country like the US, innovation is certainly one such factor. For example, looking at the list of the wealthiest individuals across US states in 2015 compiled by Forbes (Brown, 2015), 11 out of 50 are listed as inventors in a US patent and many more manage or own firms that patent. More importantly, if we look at patenting and top income inequality in the US and other developed countries over the past decades, we see that these two variables tend to follow parallel evolutions.

Thus Figure 1 below looks at patenting per 1000 inhabitants and the top 1% income share in the US since the 1960s: up to the early 1980s, both variables show essentially no trend but since then the two variables experience sharp upward trends.[2]

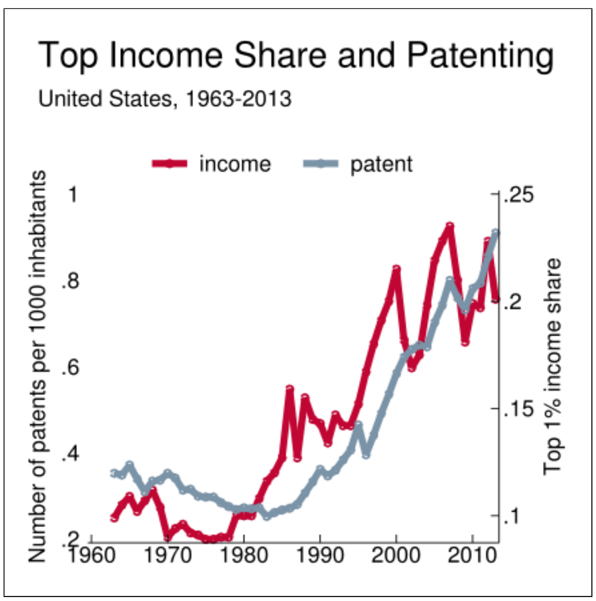

Figure 1: This figure plots the number of patent applications per 1000 inhabitant against the top 1% income share for the USA as a whole. Observations span the years 1963-2013.

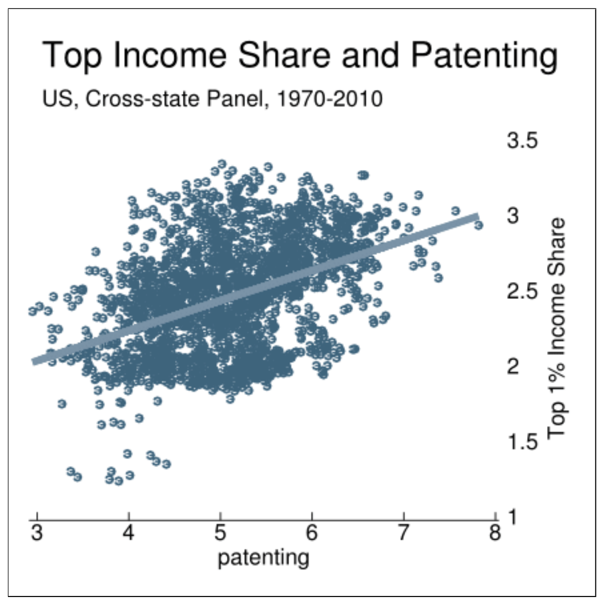

Figure 2: This figure plots the logarithm of the number of patent applications per capita (x-axis) against the logarithm of the top 1% income share (y-axis). Observations are computed at the US state level over 1975-2010.

In this paper, we use cross-state panel data over the period 1975-2010 to show that top

[1]The worldwide interest for income and wealth inequality, has been spurred by popular books such as Goldin and Katz (2009), Deaton (2014) and Piketty (2014).

[2]The figures in this introduction use unweighted patent counts as measure of innovation. Using citation-weighted patent counts yields similar patterns, although the series for unweighted patent counts are available over a longer period.

income inequality is at least partly caused by innovation, as suggested by Figure 2. Innovation is measured by the flow and/or quality of patented innovations in the corresponding US state, and top income inequality is measured by the share of income held by the top 1%.

In the first part of the paper, we develop a Schumpeterian growth model where growth results from quality-improving innovations that can be made in each sector either from the incumbent in the sector or from potential entrants. Facilitating innovation or entry increases the entrepreneurial share of income and spurs social mobility through creative destruction as employees' children more easily become business owners and vice versa. In particular, this model predicts that: (i) innovation by entrants and incumbents increases top income inequality; (ii) innovation by entrants increases social mobility; (iii) entry barriers lower the positive effects of entrants' innovations on top income inequality and social mobility.

Our main findings can be summarized as follows. First, the top 1% income share in a given US state in a given year, is positively and significantly correlated with the state's degree of innovativeness, i.e. with the quality-adjusted amount of innovation in this state in that year, as reflected by citations. Further, we show a causal effect of innovation-led growth on top incomes. We establish this result by instrumenting for innovativeness following two different strategies, first by using data on the appropriation committees of the Senate (following Aghion *et al.*, 2009) and second by relying on knowledge spillovers from the other states. Both instruments deliver similar coefficients and the effects are significant: for example, when measured by the number of patent per capita, innovativeness accounts on average for around 17% of the total increase in the top 1% income share between 1975 and 2010. We also find that in cross-state panel regressions, innovativeness is less positively or even negatively correlated with measures of inequality which do not emphasize the very top incomes, in particular the top 2 to 10% income shares (i.e. excluding the top 1%), or broader measures of inequality like the Gini coefficient or the Atkinson index, as suggested by Figure 3 below.[3] Next, we show that the positive effects of innovation on the top 1% income share are dampened in states with higher lobbying intensity. Finally, from cross-section regressions performed at the commuting zone (CZ) level, we find that: (i) innovativeness is positively correlated with upward social mobility (Figure 4 below[4]); (ii) the positive correlation between

[3]Figure 3 plots the average top-1% income share and the bottom 99% Gini index as a function of their corresponding innovation percentiles. The bottom 99% Gini is the Gini coefficient when the top 1% of the income distribution is removed. Innovation percentiles are computed using the US state-year pairs from 1975 to 2010. Each series is normalized by its value in the lowest innovation percentile.

[4]Figure 4 plots the logarithm of the number of patent applications per capita (x-axis) against the logarithm of social mobility (y-axis). Social mobility is computed as the probability to belong to the highest quintile of the income distribution in 2010 (when aged env. 30) when parents belonged to the lowest quintile in 1996 (when aged env. 16). Observations are computed at the Commuting Zones level (569 observations). The number of patents is averaged from 2006 to 2010.

innovativeness and social mobility, is driven mainly by entrant innovators and less so by incumbent innovators, and it is dampened in states with higher lobbying intensity.

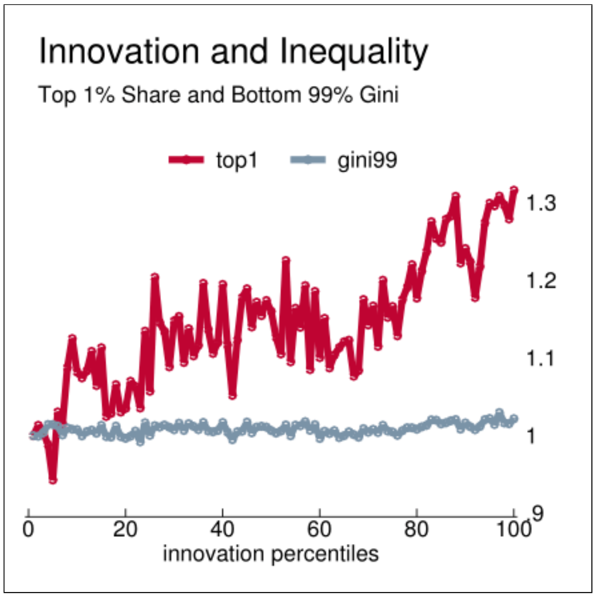

Figure 3: See footnote 3 for explanations.

Figure 4: See footnote 4 for explanations.

Our results pass a number of robustness tests: in particular the positive and significant correlation between innovativeness and top income shares in cross state panel regressions, is robust to varying the time-lags on innovation, to introducing various proxies reflecting the importance of the financial sector, to including top marginal tax rates as control variables (whether on capital, labor or interest income), and to controlling for sectors' size or for potential agglomeration effects.

The analysis in this paper relates to several strands of literature. First, to the endogenous growth literature: thus Rebelo (1991) developed an AK model to argue that (over)taxing capital can be detrimental to growth as capital accumulation amounts to knowledge accumulation in AK models. Similarly, a straightforward implication of innovation-based growth models (Romer, 1990; Aghion and Howitt, 1992) is that, everything else equal, taxing innovation rents is detrimental to growth as it discourages individuals from investing in R&D and thus from innovating. We contribute to this literature, first by introducing social mobility into the picture and linking it to creative destruction, and second by looking explicitly at the effects of innovativeness on top income shares.[5]

[5]Hassler and Rodriguez-Mora (2000) analyze the relationship between growth and intergenerational mobility in a model which may feature multiple equilibria, some with high growth and high social mobility and others with low growth and low social mobility. Multiple equilibria arise because in a high growth environment, inherited knowledge depreciates faster, which reduces the advantage of incumbents. In that paper however, growth is driven by externalities instead of resulting from innovations.

Second, our paper relates to an empirical literature on inequality and growth. Thus, Banerjee and Duflo (2003) find no robust relationship between income inequality and growth when measuring inequality by the Gini coefficient, whereas Forbes (2000) finds a positive relationship between these two variables. However, these papers do not look at top incomes nor at social mobility, and they do not contrast innovation-led growth with non-frontier growth. More closely related to our analysis, Frank (2009) finds a positive relationship between both the top 10% and top 1% income shares and growth across US states; however, Franck does not establish any causal link from growth to top income inequality, nor does he consider innovation or social mobility.[6]

Third, a large literature on skill-biased technical change aims at explaining the increase in labor income inequality since the 1970's.[7] While this literature focuses on the *direction* of innovation and on broad measure of labor income inequality (such as the skill-premium), our paper is more directly concerned with the rise of the top 1% and how it relates with the *rate* and *quality* of innovation (in fact our results suggest that innovativeness does not have a strong impact on broad measures of inequality compared to their impact on top income shares).

Fourth, our focus on top incomes links our paper to a large literature documenting a sharp increase in top income inequality over the past decades (in particular, see Piketty and Saez, 2003). We contribute to this line of research by arguing that increases in top 1% income shares, are at least in part caused by increases in innovation-led growth.[8]

Most closely related to our paper is Jones and Kim (2014), who also develop a Schumpeterian model to explain the dynamics of top income inequality. In their model, growth results from both, the accumulation of experience or knowledge by incumbents (which may in turn result from incumbent innovation) and creative destruction by entrants. The former

[6]Parallel work by Acemoglu and Robinson (2015) also reports a positive correlation between top income inequality and growth in panel data at the country level (or at least no evidence of a negative correlation).

[7]In particular, Katz and Murphy (1992) and Goldin and Katz (2008) have shown that technical change has been skill-biased in the 20^{th} century. Acemoglu (1998, 2002 and 2007) sees the skill distribution as determining the direction of technological change, while Hémous and Olsen (2014) argue that the incentive to automate low-skill tasks naturally increases as an economy develops. Several papers (Aghion and Howitt, 1997; Caselli, 1999; Galor and Moav, 2000) see General Purpose Technologies (GPT) as lying behind the increase in inequality, as the arrival of a GPT favors workers who adapt faster to the detriment of the rest of the population. Krusell, Ohanian, Ríos-Rull and Violante (2000) show how with capital-skill complementarity, the increase in the equipment stock can account for the increase in the skill premium.

[8]Rosen (1981) emphasizes the link between the rise of superstars and market integration: namely, as markets become more integrated, more productive firms can capture a larger income share, which translates into higher income for its owners and managers. Similarly, Gabaix and Landier (2008) show that the increase in the size of some firms can account for the increase in their CEO's pay. Our analysis is consistent with this line of work, to the extent that successful innovation is a main factor driving differences in productivities across firms, and therefore in firms' size.

increases top income inequality whereas the latter reduces it by allowing entrants to catch up with incumbents.[9] In our model instead, a new (entrant) innovation increases mark-ups in the corresponding sector, whereas in the absence of a new innovation mark-ups are partly eroded as a result of imitation. On the other hand, the two papers have in common the ideas: (i) that innovation and creative destruction are key factors in the dynamics of top income inequality; (ii) that fostering entrant innovation contributes to making growth more "inclusive".[10]

The remaining part of the paper is organized as follows. Section 2 outlays a simple Schumpeterian model to guide our analysis of the relationship between innovation-led growth, top incomes, and social mobility. Section 3 presents our cross-state panel data and our measures of inequality and innovativeness. Section 4 presents our core regression results. Section 5 introduces social mobility and entry barrier considerations into the analysis. And Section 6 concludes.

2 Theory

In this section we develop a simple Schumpeterian growth model to explain why increased R&D productivity or increased openness to entry increases both, the top income share and social mobility.

2.1 Baseline model

Consider the following discrete time model. The economy is populated by a continuum of individuals. At any point in time, there is a measure 2 of individuals in the economy, half of them are capital owners who own the firms and the rest of the population works as production workers.[11] Each individual lives only for one period. Every period, a new generation of individuals is born and individuals that are born to current firm owners inherit the firm from their parents. The rest of the population works in production unless they successfully innovate and replace incumbents' children.

[9]More specifically, in Jones and Kim (2014) entrants innovation only reduces income inequality because it affects incumbents' efforts. Therefore in their model an exogenous increase in entrant innovation will not affect inequality if it is not anticipated by incumbents.

[10]Indeed, we show that entrant innovation is positively associated with social mobility. Moreover, if, as we shall see below, incumbent innovation and entrant innovation contribute to a comparable extent to increasing the top 1% income share, additional regressions (available upon request from the authors) suggest that incumbent innovation contributes more to increasing the top 0.1% share than entrant innovation.

[11]One can extend the analysis to the more general case where workers' population differs from business owners' population. All our results go through except that we then have to carry around the mass of workers through all the equilibrium equations of the model.

2.1.1 Production

A final good is produced according to the following Cobb-Douglas technology:

$$\ln Y_t = \int_0^1 \ln y_{it} di, \tag{1}$$

where y_{it} is the amount of intermediate input i used for final production at date t. Each intermediate is produced with a linear production function

$$y_{it} = q_{it} l_{it}, \tag{2}$$

where l_{it} is the amount of labor used to produce intermediate input i at date t and q_{it} is the labor productivity. Each intermediate i is produced by a monopolist who faces a competitive fringe from the previous technology in that sector.

2.1.2 Innovation

Whenever there is a new innovation in any sector i in period t, quality in that sector improves by a multiplicative term η_H so that:

$$q_{i,t} = \eta_H q_{i,t-1}.$$

In the meantime, the previous technological vintage $q_{i,t-1}$ becomes publicly available, so that the innovator in sector i obtains a technological lead of η_H over potential competitors.

At the end of period t, other firms can partly imitate the (incumbent) innovator's technology so that, in the absence of a new innovation in period $t + 1$, the technological lead enjoyed by the incumbent firm in sector i shrinks to η_L with $\eta_L < \eta_H$.

Overall, the technological lead enjoyed by the incumbent producer in any sector i takes two values: η_H in periods with innovation and $\eta_L < \eta_H$ in periods without innovation.[12]

Finally, we assume that an incumbent producer that has not recently innovated, can still resort to lobbying in order to prevent entry by an outside innovator. Lobbying is successful with exogenous probability z, in which case, the innovation is not implemented, and the incumbent remains the technological leader in the sector (with a lead equal to η_L).

Both potential new entrants and incumbents have access to the following innovation

[12] The details of the imitation-innovation sequence do not matter for our results, what matters is that innovation increases the technological lead of the incumbent producer over its competitive fringe.

technology. By spending

$$C_{K,t}(x) = \theta_K \frac{x^2}{2} Y_t$$

an incumbent ($K = I$) or entrant ($K = E$) can innovate with probability x. A reduction in θ_K captures an increase in R&D productivity or R&D support, and we allow for it to differ between entrants and incumbents.

2.1.3 Timing of events

Each period unfolds as follows:

1. In each line i, a potential entrant spends $C_{E,t}(x_i)$ and the offspring of the incumbent in sector i spends $C_{I,t}(\tilde{x}_i)$.

2. With probability $(1-z)\,x_i$ the entrant succeeds, replaces the incumbent and obtains a technological lead η_H, with probability $\tilde{x}_i$ the incumbent succeeds and improves its technological lead from η_L to η_H, with probability $1-(1-z)\,x_i-\tilde{x}_i$, there is no successful innovation and the incumbent stays the leader with a technological lead of η_L.[13]

3. Production and consumption take place and the period ends.

2.2 Solving the model

We solve the model in two steps: first, we compute the income shares of entrepreneurs and workers and the rate of upward social mobility (from being a worker to becoming an entrepreneur) for given innovation rates by entrants and incumbents; second, we endogeneize the entrants' and incumbents' innovation rates.

2.2.1 Income shares and social mobility for given innovation rates

In this subsection we take as given the fact that in all sectors potential entrants innovate at some rate x_t and incumbents innovate at some rate $\tilde{x}_t$ at date t.

[13] For simplicity, we rule out the possibility that both agents innovate in the same period, so that innovations by the incumbent and the entrant in any sector, are not independent events. This can be microfounded in the following way. Assume that every period there is a mass 1 of ideas, and only one idea is succesful. Research efforts x and $\widetilde{x}$ represent the mass of ideas that a firm investigates. Firms can observe each other actions, therefore in equilibrium they will never choose to look for the same idea provided that $x^* + \widetilde{x}^* < 1$, which is satisfied for θ_K sufficiently large.

Using (2), the marginal cost of production of (the leading) intermediate producer i at time t is

$$MC_{it} = \frac{w_t}{q_{i,t}}.$$

Since the leader and the fringe enter Bertrand competition, the price charged at time t by intermediate producer i is simply a mark-up over the marginal cost equal to the size of the technological lead, i.e.

$$p_{i,t} = \frac{w_t \eta_{it}}{q_{i,t}}, \tag{3}$$

where $\eta_{i,t} \in \{\eta_H, \eta_L\}$. Therefore innovating allows the technological leader to charge temporarily a higher mark-up.

Using the fact that the final good sector spends the same amount Y_t on all intermediate goods (a consequence of the Cobb-Douglas technology assumption), we have in equilibrium:

$$Y_t = p_{i,t} y_{it} \text{ for all } i. \tag{4}$$

This, together with (3) and (2), allows us to immediately express the labor demand and the equilibrium profit in any sector i at date t.

Labor demand by producer i at time t is given by:

$$l_{it} = \frac{Y_t}{w_t \eta_{it}}.$$

And equilibrium profits in sector i at time t are equal to:

$$\pi_{it} = (p_{it} - MC_{it}) y_{it} = \frac{\eta_{it} - 1}{\eta_{it}} Y_t.$$

Hence profits are higher if the incumbent has recently innovated, namely:

$$\pi_{H,t} = \underbrace{\frac{\eta_H - 1}{\eta_H}}_{\equiv \pi_H} Y_t > \pi_{L,t} = \underbrace{\frac{\eta_L - 1}{\eta_L}}_{\equiv \pi_L} Y_t.$$

Now we have everything we need to derive the expressions for the income shares of workers and entrepreneurs and for the rate of upward social mobility. Let μ_t denote the fraction of high-mark-up sectors (i.e. with $\eta_{it} = \eta_H$) at date t.

Labor market clearing at date t implies that:

$$1 = \int l_{it} di = \int \frac{Y_t}{w_t \eta_{it}} di = \frac{Y_t}{w_t} \left[\frac{\mu_t}{\eta_H} + \frac{1 - \mu_t}{\eta_L} \right]$$

We restrict attention to the case where the η_{it}'s are sufficiently large that

$$w_t < \pi_{L,t} < \pi_{H,t},$$

so that top incomes are earned by entrepreneurs.

Hence the share of income earned by workers (wage share) at time t is equal to:

$$wages\_share_t = \frac{w_t}{Y_t} = \frac{\mu_t}{\eta_H} + \frac{1-\mu_t}{\eta_L}. \tag{5}$$

whereas the share of income earned by entrepreneurs (entrepreneurs share) at time t is equal to:

$$entrepreneur\_share_t = \frac{\mu_t \pi_{H,t} + (1-\mu_t)\,\pi_{L,t}}{Y_t} = 1 - \frac{\mu_t}{\eta_H} - \frac{1-\mu_t}{\eta_L}. \tag{6}$$

Since mark-ups are larger in sectors with new technologies, aggregate income shifts from workers to entrepreneurs in relative terms whenever the equilibrium fraction of product lines with new technologies μ_t increases. But by the law of large numbers this fraction is equal to the probability of an innovation by either the incumbent or a potential entrant in any intermediate good sector.

More formally, we have:

$$\mu_t = \tilde{x}_t + (1-z)\,x_t, \tag{7}$$

which increases with the innovation intensities of both incumbents and entrants, but to a lesser extent with respect to entrants' innovations the higher the entry barriers z are.

Finally, we measure upward social mobility by the probability Ψ_t that the offspring of a worker becomes a business owner. This in turn happens only if this individual manages to first innovate and then avoids the entry barrier; therefore

$$\Psi_t = x_t\,(1-z)\,, \tag{8}$$

which is increasing in entrant's innovation intensity x_t but less so the higher the entry barriers z are. This yields:

Proposition 1 *(i) A higher rate of innovation by a potential entrant, x_t, is associated with a higher entrepreneur share of income and a higher rate of social mobility, but less so the higher the entry barriers z are; (ii) A higher rate of innovation by an incumbent, $\widetilde{x}_t$, is associated with a higher entrepreneur share of income but has no impact on social mobility.*

Remark: That the equilibrium *share* of wage income in total income decreases with the fraction of high mark-up sectors μ_t, and therefore with the innovation intensities of

entrants and incumbents, does not imply that the equilibrium *level* of wages also declines. In fact the opposite occurs.[14] In addition, note that the entrepreneurial share is independent of innovation intensities in previous periods. Therefore, a temporary increase in current innovation only leads to a temporary increase in the entrepreneurial share: once imitation occurs, the gains from the current burst in innovation will be equally shared by workers and entrepreneurs.

2.2.2 Endogenous innovation

We now turn to the endogenous determination of the innovation rates of entrants and incumbents. The offspring of the previous period's incumbent solves the following maximization problem:

$$\max_{\tilde{x}} \left\{ \tilde{x}\pi_H Y_t + (1 - \tilde{x} - (1-z)\, x^*)\, \pi_L Y_t + (1-z)\, x^* w_t - \theta_I \frac{\tilde{x}^2}{2} Y_t \right\}.$$

This expression states that the offspring of an incumbent can already collect the profits of the firm that she inherited (π_L), but also has the chance of making higher profit (π_H) by innovating with probability $\tilde{x}$.

Clearly the optimal innovation decision is simply

$$\tilde{x}_t^* = \tilde{x}^* = \frac{\pi_H - \pi_L}{\theta_I} = \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right) \frac{1}{\theta_I}, \tag{11}$$

which decreases with incumbent R&D cost parameter θ_I.

[14] To see this more formally, we can compute the equilibrium level of wages by plugging (4) and (3) in (1), which yields:

$$w_t = \frac{Q_t}{\eta_H^{\mu_t} \eta_L^{1-\mu_t}}, \tag{9}$$

where Q_t is the quality index defined as $Q_t = \exp \int_0^1 \ln q_{it} di$. The law of motion for the quality index is computed as

$$Q_t = \exp \int_0^1 \left[\mu_t \ln \eta_H q_{it-1} + (1-\mu_t) \ln q_{it-1} \right] di = Q_{t-1} \eta_H^{\mu_t}. \tag{10}$$

Therefore, for given technology level at time $t-1$, the equilibrium wage is given by

$$w_t = \eta_L^{\mu_t - 1} Q_{t-1}.$$

This last equation clearly shows that the overall effect of a current increase in innovation intensities is to increase the equilibrium wage for given technology level at time $t-1$, even though it also shifts some income share towards entrepreneurs

A potential entrant in sector i solves the following maximization problem:

$$\max_{x}\left\{(1-z)\,x\pi_H Y_t+(1-x\,(1-z))\,w_t-\theta_E\frac{x^2}{2}Y_t\right\},$$

since a new entrant chooses its innovation rate with the outside option being a production worker who receives wage w_t.

Using equation (5), taking first order conditions, and using our assumption that $w_t<\pi_{L,t}$, we can express the entrant innovation rate as

$$x_t^*\equiv x^*=\left(\pi_H-\left[\frac{\mu_t}{\eta_H}+\frac{1-\mu_t}{\eta_L}\right]\right)\frac{(1-z)}{\theta_E}. \tag{12}$$

Then, since in equilibrium

$$\mu^*=(1-z)\,x^*+\tilde{x}^*,$$

and using the fact that entrants do innovate in equilibrium (as we restrict attention to parameter values for which $\pi_H>w$), the equilibrium innovation rate for entrants is simply given by

$$x^*=\frac{\left(\pi_H-\frac{1}{\eta_L}+\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\tilde{x}^*\right)(1-z)}{\theta_E-(1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)}. \tag{13}$$

Therefore lower barriers to entry (i.e. a lower z) and less costly R&D for entrants (lower θ_E) both increase the entrants' innovation rate (as $1/\eta_L-1/\eta_H>0$). Less costly incumbent R&D also increases the entrant innovation rate since $\widetilde{x}^*$ is decreasing in θ_I.[15]

Intuitively, high mark-up sectors are those where an innovation just occurred and was not blocked, so a reduction in either entrants' or incumbents' R&D costs increases the share of high mark-up sectors in the economy and thereby the entrepreneurs' share of income. And to the extent that higher entry barriers dampen the positive correlation between the entrants' innovation rate and the entrepreneurial share of income, they will also dampen the positive effects of a reduction in entrants' or incumbents' R&D costs on the entrepreneurial share of income.[16]

Finally, equation (8) immediately implies that a reduction in entrants' or incumbents' R&D costs increases social mobility but less so the higher the barriers to entry are.

We have thus established:

[15] That x^* increases with $\widetilde{x}^*$ results from the fact that more innovation by incumbents lowers the equilibrium wage which decreases the opportunity cost of innovation for an entrant. This general equilibrium effect rests on the assumption that incumbents and entrants cannot both innovate in the same period.

[16] See the proof of Proposition 2 below.

Proposition 2 *An increase in R&D productivity (whether it is associated with a reduction in θ_I or in θ_E), leads to an increase in the innovation rates x^* and $\tilde{x}^*$ but less so the higher the entry barriers z are; consequently, it leads to higher growth, higher entrepreneur share and higher social mobility but less so the higher the entry barriers are.*

Proof. The only claim we have not formally proved in the text is that $\frac{\partial^2}{\partial\theta_K \partial z}(1-z)\,x^* > 0$ (which immediately implies that the positive impact of an increase in R&D productivity on growth, entrepreneurial share and social mobility is attenuated when barriers to entry are high). Differentiating first with respect to θ_E, we get:

$$\frac{\partial (1-z)\,x^*}{\partial \theta_E} = -\frac{(1-z)\,x^*}{\theta_E - (1-z)^2\left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)},$$

which is increasing in z since x^* and $(1-z)$ both decrease in z and the denominator $\theta_E + (1-z)^2\left[\frac{1}{\eta_H} - \frac{1}{\eta_L}\right]$ increases in z (recall that $\frac{1}{\eta_L} - \frac{1}{\eta_H} > 0$). Similarly, differentiating with respect to θ_I gives:

$$\frac{\partial (1-z)\,x^*}{\partial \theta_I} = \frac{\left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)(1-z)}{\theta_E - (1-z)^2\left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)}\frac{\partial \tilde{x}^*}{\partial \theta_I},$$

which is increasing in z since $\frac{\partial \tilde{x}^*}{\partial \theta_I} < 0$, and $1-z$ and the denominator both decrease in z. This establishes the proposition. ■

2.2.3 Impact of mark-ups on innovation and inequality

Our discussion so far pointed to a causality from innovation to top income inequality and social mobility. However the model also speaks to the reverse causality from top inequality to innovation. First, a higher innovation size η_H leads to a higher mark-up for firms which have successfully innovated. As a result, it increases the entrepreneur share for given innovation rate (see (6)). Second, a higher η_H increases incumbents' (11) and (13) entrants' innovation rates, which further increases the entrepreneur share of income.[17]

[17] More interestingly perhaps, a higher η_L increases the mark-up of non-innovators, and thereby increases the entrepreneur share for a given innovation rate (see (6) and recall that $(1-z)\,x^* + \tilde{x}^* < 1$). Yet, it decreases incumbents' innovation rate since their net reward from innovation is lower. In the special case where $\theta_I = \theta_E$ this leads to a decrease in the total innovation rate (see the Appendix). For a sufficiently high R&D cost (θ high), the overall impact on the entrepreneur share remains positive. Therefore a higher η_L can contribute to a negative correlation between innovation and the entrepreneur share.

2.3 Predictions

We can summarize the main predictions from the above theoretical discussion as follows.

- Innovation by both entrants and incumbents, increases top income inequality;
- Innovation by entrants increases social mobility;
- Entry barriers lower the positive effect of entrants' innovation on top income inequality and on social mobility.

Before we confront these predictions to the data, note that the above model also predicts that national income shifts away from labor towards firm owners as innovation intensifies. This is in line with findings from the recent literature on declining labor share (e.g. see Elsby et al. (2013) and Karabarbounis and Neiman (2014)). In fact Figures 5 and 6 show that over the past forty years in the US, the profit share increased and the labor share decreased (one minus the labor share increased) in ways that paralleled the acceleration in innovation. This provides additional support for our model.

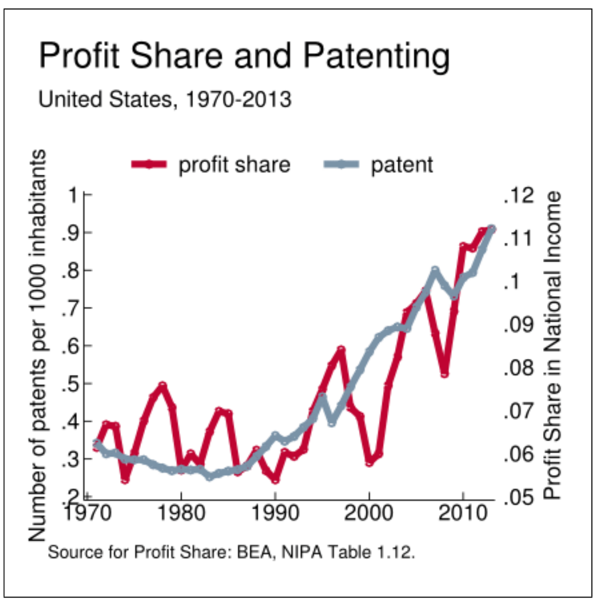

Figure 5: Profit Share in National Income

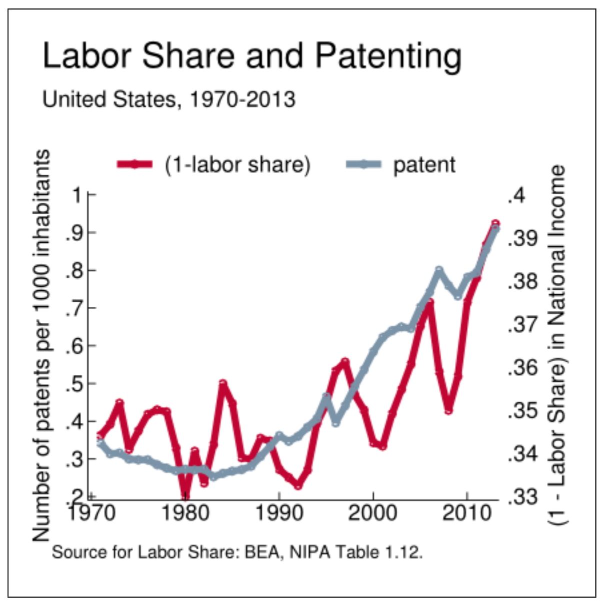

Figure 6: Labor Share in National Income

3 Data and measurement

Our core empirical analysis is carried out at US state level. Our dataset covers the period 1975-2010, a time range imposed upon us by the availability of patent data.

3.1 Inequality

The data on the share of income owned by the top 1% of the income distribution for our cross-US-state panel analysis, are drawn from the US State-Level Income Inequality Database (Frank, 2009). From the same data source, we also gather information on alternative measures of inequality: namely, the top 10% income share, the Atkinson Index (with a coefficient of 0.5), the Theil Index and the Gini Index. We thus end up with a balanced panel of 51 states (we include Alaska and Hawaii and count the District of Columbia as a "state") and a total of 1836 observations (51 states over 36 years). In 2010, the three states with the highest share of total income held by the richest 1% are Connecticut, New York and Wyoming with respectively 21.7%, 21.1% and 20.1% whereas West Virginia, Iowa and Maine are the states with the lowest share held by the top 1% (respectively 11.8%, 12% and 12%). In every US state, the top 1% income share has increased between 1975 and 2010, the unweighted mean value was around 8% in 1975 and reached 21% in 2007 before slowly decreasing to 16.3% in 2010. In addition, the heterogeneity in top income shares across states is larger in the recent period than it was during the 1970s, with a cross-state variance multiplied by 2.7 between 1975 and 2010.

Note that the US State-Level Income Inequality Database provides information on the adjusted gross income from the IRS. This is a broad measure of pre-tax (and pre-transfer) income which includes wages, entrepreneurial income and capital income (including realized capital gains). Unfortunately it is not possible to decompose total income in the various sources of income (wage, entrepreneurial or capital incomes) with this dataset. In contrast, the World Top Income Database (Alvaredo et al., 2014), allows us to assess the composition of the top 1% income share. On average between 1975 and 2010, wage income represented 50.7% and entrepreneurial income 19.1% of the total income earned by the top 1% (with entrepreneurial income having a lower share in later years), while for the top 10%, wage income represented 71.1% and entrepreneurial income 11.7% of total income. In our model, entrepreneurs are those directly benefitting from innovation. In practice, innovation benefits are shared between firm owners, top managers and inventors, thus innovation affects all sources of income within the top 1%. Yet, the fact that entrepreneurial income is overrepresented in the top 1% income relative to wage income, suggests that our model captures an important aspect in the evolution of top income inequality.

3.2 Innovation

When looking at cross state or more local levels, the US patent office (USPTO) and the HBS patent database from Lai et al. (2013) provide complete statistics for patents granted between the years 1975 and 2010. For each patent, it provides information on the state of residence of the patent *inventor*, the date of application of the patent and a link to every citing patents granted before 2010. This citation network between patents enables us to construct several estimates for the quality of innovation as described below. Since a patent can be associated with more than one inventor and since coauthors of a given patent do not necessarily live in the same state, we assume that patents are split evenly between inventors and thus we attribute only a fraction of the patent to each inventor. A patent is also associated with an *assignee* that owns the right to the patent. Usually, the assignee is the firm employing the inventor, and for independent inventors the assignee and the inventor are the same person. We chose to locate each patent according to the US state where its inventor lives and works. Although the inventor's location might occasionally differ from the assignee's location, most of the time the two locations coincide (the correlation between the two is above 92%).[18] Moreover, we checked that all our results are robust to locating patents according to the assignee's address instead of the inventor's address. And we also checked the robustness of our results to removing independent inventors from the patent count. Finally, in line with the patenting literature, we focus on "utility patents" which cover 90% of all patents at the USPTO.[19]

3.2.1 Truncation bias

The so-called truncation bias in patent count stems from the fact that the process of granting a patent takes about two years on average following patent application. As the individual USPTO database contains only patents that have been granted before 2010, simply grouping by state for each year will lead to underestimate the intensity of innovation as we approach the end period of the sample (as many patents with application dates close to 2010 are unlikely to be granted by 2010, and therefore to appear in the database). Since we restrict attention to patents with application dates between 1975 and 2010, the truncation bias is not

[18]For example, Delaware and DC are states for which the inventor's address is more likely to differ from the assignee's address.

[19]The USPTO classification considers three types of patents according to the official documentation: utility patents that are used to protect a new and useful invention, for example a new machine, or an improvement to an existing process; design patents that are used to protect a new design of a manufactured object; and plant patents that protect some new varieties of plants. Among those three types of patents, the first is presumably the best proxy for innovation, and it is the only type of patents for which we have complete data.

an issue at the beginning of the time period (correcting for patents that were granted after 1975 but with application dates before 1975). To account for truncation, we use aggregate data on patent granted by application date at the state level from the USPTO website. These data are updated on a yearly basis and thus should contain every patent up to 2006.[20] We note that in the last decade the USPTO has faced a large surge in the number of patent applications as evidenced by the official statistics on the number of applications (regardless whether these patents will ultimately be granted or not). Consequently, a growing share in the number of applications filed are still pending because they have not yet been examined (for more information about this backlog, see De Rassenfosse et al. (2013)). To address this problem, we completed the series after 2006 with the adjusted number of patent applications by the various states (regardless of whether the patents were to be granted or rejected) from the Strumsky Granted Patent and Patent Application Database[21] assuming a constant and homogeneous rate of acceptance for the years 2007, 2008, 2009 and 2010. This assumption is not unreasonable when looking at past data. This method has its shortcomings though: the measure is noisy for the last three years as it may involve including many insignificant patents. An alternative would be to assume that the backlog accounts for the same share of patents across all states, which in turn is consistent with the shape of the lag distribution being very similar across states. But then, the backlog would be captured by our fixed effects. Fortunately, these two approaches yield very similar results and therefore we shall only present results using the first approach.[22]

Similarly, we correct for truncated citation bias using the quasi-structural approach proposed by Hall, Jaffe and Trajtenberg (2001) and extend their HJT corrector until 2010. This method allows us to correct for the citation truncation bias and to generate citation data that can be compared over time. Here again, because of the inaccuracy of the correction variable for the last three years, corrected citation counts can mainly be used before 2008.

3.2.2 Quality measures

Simply counting the number of patent granted by their application date is a crude measure of innovation as it does not differentiate between a patent that made a significant contri-

[20]According to the USPTO website: *"As of 12/31/2012, utility patent data, as distributed by year of application, are approximately 95% complete for utility patent applications filed in 2004, 89% complete for applications filed in 2005, 80% complete for applications filed in 2006, 67% complete for applications filed in 2007, 49% complete for applications filed in 2008, 36% complete for applications filed in 2009, and 19% complete for applications filed in 2010; data are essentially complete for applications filed prior to 2004."* By the same logic, in 2014 nearly all patents from 2006 should be included.

[21]https://clas-pages.uncc.edu/innovation/

[22]Yet another approach is to delete the time component by considering only the share of total patents application in each state. We checked the robustness of our results to using this alternative approach.

bution to science and a more incremental one. The USPTO database, provides sufficiently exhaustive information on patent citation to compute indicators which better measure the quality of innovation. We consider four measures of innovation quality:

- *3, 4 and 5 year windows citations counter* : this variable measures the number of citations received within no more than 3, 4 or 5 years after the application date. This measure has the advantage of being immune from the citation truncation bias problem described above as long as we correct for the number of patents and provided we stop our data sample at patents applied in 2006, 2005 and 2004 respectively.

- *Is the patent among the 5% most cited in the year by 2010?* This is a dummy variable equal to one if the patent applied for in a given year belong to the top 5% most cited patents. Because most of the patents are not yet cited, or at most once, in 2008, 2009 and 2010, we stop computing this measure after the year 2007.

- *Total corrected citation counter:* This measures the number of times a patent has been cited, once this number has been corrected for the truncation citation bias as explained above.

- *Has the patent been renewed?* This is a dummy variable equal to one if the patent has been renewed (at least once) before 2014. Indeed, USPTO require inventors to pay maintenance fees three times during the lifetime of the patent, the first payment being made three years after the date of issue. Hence this measure is immune from truncation bias issues.

These measures have been aggregated at the state level by taking the sum of the quality measures over the total number of patents granted for a given state and a given application date and then divided by the number of inhabitants. Most of our quality measures can thus be considered as citation weighted patents counts. These different measures of innovativeness display consistent trends: hence the four states with the highest flows of patents between 1975 and 1990 are also the four states with the highest total citation counts, and similarly for the five most innovative states between 1990 and 2009.

3.3 Control variables

When regressing top income shares on innovativeness, a few concerns may be raised. First, the business cycle is likely to have direct effects on innovation and top income share. Second, top income share groups are likely to involve to a significant extent individuals employed

by the financial sector (see for example Philippon and Reshef, 2012). In turn, the financial sector is sensitive to business cycles and it may also affect innovation directly. To address these two concerns, we control for the output gap and for the share of GDP accounted for by the financial sector per inhabitant. In addition, we control for the size of the government sector which may also affect both top income inequality and innovation. To these we add usual controls, namely GDP per capita and the growth of total population.

Data on GDP, total population and the share of the financial and public sectors can be found in the Bureau of Economic Analysis (BEA) regional accounts. Finally, we compute the output gap defined as the relative distance of real GDP per capita to its filtered value computed with a HP filter of parameter λ equal to 6.25. To deal with the issue of extreme values at the beginning and the end of the period, we calculated this filter over the period 1970-2013.

4 Main empirical analysis: the effect of innovativeness on top incomes

4.1 Estimation strategy

We seek to look at the effect of innovativeness measured by the flow of patents granted by the USPTO per thousand of inhabitants and by the quality of innovation on top income shares. We thus regress the top 1% income share on our measures of innovativeness. Our estimated equation is:

$$\log(y_{it}) = A + B_i + B_t + \beta_1 \log(innov_{i(t-1)}) + \beta_2 X_{it} + \varepsilon_{it}, \tag{14}$$

where y_{it} is the measure of inequality, B_i is a state fixed effect, B_t is a year fixed effect, $innov_{i(t-1)}$ is innovativeness in year $t-1$,[23] and X is a vector of control variables.[24] By including state and time fixed effects we are eliminating permanent cross state differences in inequality and also aggregate changes in inequality. We are essentially studying the relationship between the differential growth in innovation across states with the differential growth in inequality.

[23]We discuss the choice of lagged innovation variable(s) below.

[24]When *innov* is equal to 0, computing $\log(innov)$ would result in removing the observation from the panel. In such cases, we proceed as in Blundell *et al.* (1995) and replace $\log(innov)$ by 0 and add a dummy equal to one if *innov* is equal to 0. All the results of this paper are consistent with simply removing the observation and the magnitudes are only very slightly altered. This dummy is not reported.

4.2 Results from OLS regression

Table 2 presents the results from regressing top income shares and other inequality measures on the flow of patents. The relevant variables are defined in Table 1. As explained in the previous section, the number of patents granted by the USPTO for a given application date has been corrected for the truncation bias.

From Table 2 we see that the effect of the flow of patents per capita on the top 1% income share is always positive and significant at the cross state level. The effect is robust to adding the control variables even when we control for the size of the financial sector and for the size of the government.

Table 3 shows the effect of our various measures of innovation quality on the top 1% income share. The first three columns present our results when using the 3, 4 and 5 year window citation number as our innovation quality measure. As argued above, this measure has the advantage of being immune to the citation truncation bias problem as long as we restrict our observations to before 2007, 2006 and 2005 respectively for these three measures.

The results from Table 3 show that these measures of innovation quality are positively correlated with the top 1% income share. Columns 4, 5 and 6 from the same table consider the other three measures of innovation quality. Column 4 regresses top income share on the corrected number of citations per capita, column 5 regresses top income share on the number of patents among the 5% most cited in the same application year, and column 6 regresses the top income share on the number of patents per capita but counting only those that have been renewed at least once. In all instances, we find a positive and significant coefficient for innovation on the top 1% income share. Moreover, the coefficients are quite similar across the different measures of innovation.

4.3 Results from IV regressions

To deal with endogeneity issues in the regression of top income inequality on innovativeness, we construct two instruments: the first instrument relies on states' representation in the Appropriation Committees of the Senate and the House of Representatives. The second instrument exploits knowledge spillovers across states.

4.3.1 Instrumentation using the state composition of appropriation committees

Following Aghion et al (2009), we consider the time-varying State composition of the appropriation committees of the Senate and the House of Representatives. To construct this instrument, we gather data on membership of these committees over the period 1969-2010

(corresponding to Congress numbers 91 to 111).[25] The rationale for using this instrument is analyzed at length in Aghion et al. (2009): in a nutshell, the appropriation committees allocate federal funds to research education across US states.[26] A member of Congress who sits in such a Committee often pushes towards subsidizing research education in the state in which she has been elected, in order to increase her chances of reelection in that state. Consequently, a state with one of its congressmen seating on the committee is likely to receive more funding and to develop its research education, which should subsequently increase its innovativeness in the following years.

For the years 1969-2010, the number of seats in this committee has slowly increased from around 50 to 65 for the House and from around 25 to 30 for the Senate. The State composition of the Appropriation Committees is potentially a good instrument for research education subsidies and thus for innovativeness, because changes in the composition of the appropriation committees have little to do with growth or innovation performance in those states. Instead, they are determined by events such as elections or more unexpectedly the death or retirement of current heads or other members of these committees, followed by a complicated political process to find suitable candidates. This process in turn gives large weight to seniority considerations with also a concern for maintaining a fair political and geographical distribution of seats (as described with more details in Aghion et al., 2009). In addition, legislators are unable to fully evaluate the potential of a research project and are more likely to allocate grants on the basis of political interests. Both explain why it is reasonable to see the arrival of a congressman in the appropriation committee in the Senate or the House of Representatives, as an exogenous shock on innovativeness (a decrease in θ_E and θ_I in the context of our model).[27]

Based on these Appropriation Committee data, different instruments for innovativeness

[25] Data have been collected and compared from various documents published by the House of Representative and the Senate, namely: http://democrats.appropriations.house.gov/uploads/House_Approps_Concise%_History.pdf. and http://www.gpo.gov/fdsys/pkg/CDOC-110sdoc14/pdf/CDOC-110sdoc14.pdf. The name of each congressman has been compared with official biographical informations to determine the appointment date and the termination date.

[26] Even though these appropriations committees are not explicitly dedicated to research education, de facto an important fraction of their budget goes to research education. As explained in Aghion et al (2009), "research universities are important channels for pay back because they are geographically specific to a legislator's constituency.(...) Other potential channels include funding for a particular highway, bridge, or similar infrastructure project located in the constituency". We control for highway, infrastructure and military expenditures in our regressions, as explained below.

[27] A related concern is that the composition of the appropriation committee would reflect the dispropotionate attractivity of states like CA and MA. However: (i) Alabama is a state which is well represented in the committee; (ii) we use the Senate committee, and there cannot be more than two senators per state. In particular, our results could harldly be driven by CA which had no committee member until the early 1990s and thereafter had only two representatives on the committee.

can be constructed. We follow the simplest approach which is to take the number of senators (0, 1 or 2) or representatives who seat on the committee for each state and at each date.[28] Next, we need to find the appropriate time-lag between a congressman's accession into the appropriation committee and the effect this may have on innovativeness. According to Aghion *et al.* (2009), many politicians in the United States are on a two year cycle. When appointed to the committee, they must do everything in order to show their electors that they are capable of doing something for them, and will thus allocate funds to universities located in his/her states of constituency. For this reason, we decided to set the lag to two years, but one and three year lags are also considered because of the time before the allocation of new funds and the filling of a patent application.

Although changes in the composition of the Appropriation Committees can be seen as exogenous shocks on innovativeness there is still a concern about potential effects of such changes on the top 1% income share that do not relate to innovation. There is not much data on appropriation committee earmarks; yet, for the years 2008 to 2010, the Taxpayers for Common Sense, a nonpartisan budget watchdog, reports data on earmarks in which we can see that infrastructure, research, education and military are the three main recipients for appropriation committees' funds. In addition, when looking more closely at top recipients, we find that most are either universities or defense related companies.[29],[30]

Our results for the effect of innovativeness on the top 1% income share in the corresponding IV regressions are shown in Table 4.[31] We chose to present the results only for the top 1% and for the instrument using the number of seats at the Senate. Adding the number of seats occupied at the House of Representative shows consistent results but decreases the first stage F stat.[32]

[28] We checked that our results are consistent with two other measures: one which focuses on the subcommittees which are the most active in allocating federal spending: Agriculture, Defense and Energy (following Aghion et al., 2009), and another one which only considers the number of members whose seniority is less than 8 years (as these members are more likely to direct funds to their states for political reasons).

[29] Such data can be found on the *Opensecrets* website : https://www.opensecrets.org/earmarks/index.php

[30] One can of course imagine a situation in which the (rich) owner of a construction or military company will capture part of these funds. In that case, the number of senators seating in the committee of appropriation would be correlated with the top 1% income share, but for reasons having little to do with innovation. To deal with such possibility, we use data on federal allocation to states by identifying the sources of state revenues (see Aghion et al., 2009). Such data can be found at the Census Bureau on a yearly basis. Using this source, we identify a particular type of infrastructure spending, namely highways, for which we have consistent data from 1975 onward. We thus control for highways and also for the share of the federal military funding allocated to the various states.

[31] As we have a long time series for each state, we are not concerned about 'short T' bias in panel data IV. We apply instrumental variables estimator directly to equation (14).

[32] Looking at earmarks data, we can see that the senate appropriation committee (although smaller than the house of representative's committee) send more earmarks. This might be one reason for why using the Senate Appropriation Committee variable yields better first stage results.

Columns 1 to 3 show the effect of the number of patents per capita (variable *patent_pc*) on top 1% income share while columns 4 to 6 use the number of citations in a 3 year windows per capita (variable *3YWindow*).[33] The effect is positive and significant whether we consider 1, 2 or 3 year lags. First stage regression F-statistics are reported at the bottom of Table 4.[34]

In addition, the share of the financial sector is, as expected, positively correlated with the top 1% income share whereas the share of the public sector affects top income inequality negatively.

As already stressed above, changes in the appropriation committee are hard to predict. Yet, one might raise the possibility that some talented and rich inventors learn about a representative from another state having just been elected on the appropriation committee, and subsequently decide to move to that state so as to benefit from future earmarks. This would enhance the positive correlation between top income inequality and innovation although not for the reason to be captured by our IV strategy.[35] However, building on Lai et al. (2013), we were able to identify the location of successive patents by a same inventor. This in turn allowed us to delete patent observations pertaining to inventors whose previous patent was not registered in the same state. Our results still hold when we look at the effect of patents per capita on the top 1%, with a regression coefficient which is essentially the same as before (equal to 0.154).[36]

4.3.2 Instrumentation using the knowledge spillovers

To add further evidence of a causal link from innovativeness to top income shares, we exploit a second instrument based on knowledge spillovers. The idea is to instrument innovation in a state by the sum of innovation intensities in other states weighted by the propensity to cite patents from these other states. Citations reflect past knowledge spillovers, hence a citation network reflects channels whereby future knowledge spillovers occur. Knowledge spillovers

[33]Results for other measures of innovativeness are consistent and available upon request.

[34]It may seem surprising that an appointment on the appropriation committee should already have an impact on innovation after only one year. Note that separating between universities patent and non-university patents, we did find that the impact after one year was stronger on the former type. In addition, this is consistent with Toole (2007) who shows that in the pharmaceutical industry, the positive impact of public R&D on private R&D is the strongest after 1 year.

[35]Moretti and Wilson (2014) indeed showed that in the biotech industry, the decline in the user cost of capital in some US states induced by federal subsidies to those states, generated a migration of star scientists into these states.

[36]The Bayh-Dole Patent and Trademark Amendments Act of 1980 allowed universities to obtain patents on research funded by the federal governments. This could have affected the (first-stage) relationship between the composition of the Appropriation Committees and a state's innovativeness. However, removing the first few years from the estimation does not change our baseline results.

in turn lower the costs of innovation (in the model this corresponds to a decrease in θ_I or θ_E). For example, patents applied from Massachusetts in 2001 have made 56109 citations to patents outside Massachusetts. Among those citations, 1622 (3%) are made to patents applied from Florida before 2001. Thus, the relative influence of Florida on Massachusetts in 2001 in terms of innovation spillover can be set at 3%.

We then compute the matrix of weights by averaging bilateral innovation spillovers between each pair of states over the period from 1970 to 1978.[37] With such matrix, we compute our instrument as follows: if $m(i,j,t)$ is the number of citations from a patent in state i, with an application date t, to a patent of state j, and if $innov(j,t)$ denotes our measure of innovation in state j at time t, then we posit:

$$w_{i,j} = \frac{m(i,j,T)}{\sum\limits_{k \neq i} m(i,k,T)} \text{ and } KS_{i,t} = \frac{1}{Pop_{-i,t}} \sum_{j \neq i} w_{i,j} * innov(j,t-1),$$

where T is the length of the period (1970-1978) used to compute the weights $w_{i,j}$, $Pop_{-i,t}$ is the population of all states except state i and KS is the instrument.[38,39]

Table 5 presents the results when the logarithm of KS is used to instrument for the logarithm of our various measures of innovativeness: the number of patents in column 1, the number of citations received within a 3, 4 or 5 year windows in columns 2, 3 and 4 respectively, the total number of citations in column 5, and the number of patent within the 5% most cited in the year in column 6. The coefficients are always positive and significant.[40]

Reverse causality from top income inequality to this knowledge spillover IV seems unlikely (the top 1% income share in one state is unlikely to cause innovations in other states).[41] One may also worry that this instrument captures regional or industry trends that are not

[37] Indeed we observe patents whose application date is before 1975 as long as they were granted after 1975.

[38] We normalize our spillover measures for each state by the total population across the other US states. Without this correction, our measure of spillovers would mecanically put at a relative disadvantage a state which is growing relatively faster than other states. Nevertheless, our results still hold without it.

[39] Our results are also robust to adding the 2 year lag innovation as a control, in order to make sure that our instrument does not only capture lagged innovation, and to removing California from the sample, which is the most important state in our weighting.

[40] The negative and significant coefficient on per capita GDP may reflect the effect of some omitted variable like education which would affect per capita GDP postively and top income inequality negatively. In fact, when we control for the number of students per capita, this negative coefficient is largely reduced and is no longer significant while all our results remain consistent. In any case, the coefficient of innovation remains unchanged when we remove per capita GDP from the set of control variables. This in turn suggests that whatever causes the coefficient on per capita GDP to be negative, does not interfere in any major way with the effect of innovativeness on top income inequality.

[41] Yet, reverse causality might arise from the same firm citing itself across different states. We check that this has, if anything, a very marginal effect by removing citations from a firm to itself in two different states when constructing the weights: these results are essentially unaffected by this change.

directly the result of innovation and yet affect both top income inequality and innovation in that state. However, we do control for state-level per capita GDP and for the output gap, which both capture such trends.[42] In addition, using the same weights as before, we calculate and then control for a weighted average of other states' per capita GDP (variable $Spill\_Gdppc$). Finally, the weights $w_{i,j}$ are only weakly correlated with the distance between states (the coefficient is a little less than 0.2). Overall, our two instrumentation strategies, based respectively on the appropriation committee composition and on cross-state innovation spillovers, suggest a causal link between innovativeness and the top 1% income share.[43]

One might question the fact that some of our control variables are endogenous and that, conditional upon them, our instruments may be correlated with the unobservables in our model. To check that this is not the case, we re-run our IV regressions, both with each instrument separately and with both instruments jointly, with state and year fixed effects but removing the control variables. And in each case we find that the coefficient of innovation is only slightly altered compared to when we run the corresponding IV regressions with all the control variables. For example, when using our two instruments jointly on the number of patent per capita the regression coefficient varies from 0.179 when we include the control variables to 0.173 when we exclude them. The same is true when we run our IV regressions with all the control variables but instrumenting each control variable by its 1 year lag value: the coefficients on innovation are almost identical to those in the baseline IV regressions.[44]

It is also remarkable that our two instruments yield very similar estimates for the impact of innovation on top income inequality (e.g. the coefficient is 0.166 in Table 4 versus 0.162 in Table 5), all the more since the two estimations rely on very different sources of variation: controlling for year and state fixed effects, the correlation between the two instruments is very low (-5.8%). Note also that the magnitudes of the coefficients are larger than in the OLS case. This latter finding suggests that the OLS coefficients are biased downward, possibly as the result of some omitted variables that increase top income inequality but adversely effect innovation.[45]

[42]Moreover, we show in Section 4.5 that controlling for the size of additional sectors like computer manufacturing or chemistry does not affect our results.

[43]When the two instruments are used together, the effect of innovativeness on the top 1% income share remains positive and significant. The first stage F stat is a little lower than with the Senate Committee of Appropriation instrument but still acceptable. Finally, there is no evidence of overidentification when the Sargan-Hansen test is used. Column (1) of Table 6 shows the IV regression of top income inequality on the 3-Year Window when the two instruments are combined, whereas column (1) of Table 7 shows the cooresponding IV regression of top income inequality on patent count per capita).

[44]The key assumption is that the unobservables in the model are mean independent of the instruments conditional on the included controls.

[45]Such variables may typically include entry barriers (e.g. associated with lobbying or corruption) that affect innovation by entrants negatively and yet contribute to increasing top income inequality by enhancing

More details on the IV regressions (including the first stage and reduced form results) are available in the Appendix.

4.3.3 Magnitude of the effects

The above results suggest a causal effect of innovativeness on top income shares at the cross state panel level. At this stage it is worth setting back and looking at the magnitude of this effect. From our IV regressions in Tables 4 and 5, we see that an increase in 1% in the number of patents per capita increases the top 1% income share by 0.17% and that the effects of a 1% increase in the citation-based measures are of comparable magnitude. This means for example that in California where the flow of patents per capita has been multiplied by 3 and the top 1% income share has been multiplied by 2.3 from 1975 to 2009, the increase in innovativeness can explain 22% of the increase in the top 1% income share over that period. On average across US states, the increase in innovativeness as measured by the number of patents per capita explains about 17% of the total increase in the top 1% income share over the period between 1975 and 2010. Looking now at cross state differences in a given year, we can compare the effect of innovativeness with that of other significant variables such as the importance of the financial sector. Our IV regressions suggest that if a state were to move from the first quartile in terms of the number of patents per capita in 2000[46] to the fourth quartile, its top 1% income share would increase on average by 1.5 percentage points. Similarly, moving from the first to the fourth quartile in terms of the number of citations, increases the top 1% income share by 1.6 percentage points. By comparison, moving from the first quartile in terms of the size of the financial sector to the fourth quartile, would lead to a 1.0 percentage point increase in the top 1% income share.

Our results are likely to understate the true impact of innovation on top income inequality at the national level for at least two reasons. First, if successful, an innovator from a relatively poor state, is likely to move to a richer state, and therefore not contribute to the top 1% share of her own state. Second, an innovating firm may have some of its owners and top employees located in a state different from that of inventors, in which case the effect of innovativeness on top income inequality will not be fully internalized by the state where the

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incumbents' rents. As shown below, lobbying is indeed positively correlated with the top 1% income share and negatively correlated with the flow of patents. Accordingly, our theoretical model predicts that higher mark-ups by non-innovator incumbents can have a positive impact on inequality but a negative one on innovation. Inequality by itself may cause lower innovation, for instance if concentrated wealth negatively impacts innovation by poor credit-constrained individuals. Finally, measurement errors provide an additional explanation for a downward bias of the OLS coefficients, especially to the extent that the relationship between our measure of innovation quality and the revenues generated by an innovation may be quite noisy.

[46] We chose 2000 as a reference year because it is the last year for which we have non corrected patents data. Results remain consistent when the reference year changes.

patent is registered.[47] Nevertheless, overall we find a sizeable effect of innovativeness on top income inequality.

4.4 Other measures of inequality

In this section, we perform the same regressions as before but using broader measures of inequality: the top 10% income share, the Gini coefficient, the Atkinson index, the Theil index and the Relative Mean Deviation of the distribution of income, which are drawn from Frank (2009). Moreover, with data on the top 1% income share, we derive an estimate for the Gini coefficient of the remaining 99% of the income distribution, which we denote by $G99$ where:

$$G99 = \frac{G - top1}{1 - top1},$$

where G is the global Gini and top1 is the top 1% income share. In order to check if the effect of innovativeness on inequality is indeed concentrated on the top 1% income, we compute the average share of income received by each percentile of the income distribution from top 10% to top 2% and compare the coefficient on the regression of innovation on this variable with the one obtained with the top 1% income share as left hand side variable. This average size is equal to:

$$Avgtop = \frac{top10 - top1}{9}$$

where top10 represents the size of the top 10% income share. Table 6 shows the results obtained when regressing these other measures of inequalities on innovation quality.[48] In this table we instrument innovativeness using our two types of instruments, namely the two year lag in the appropriation committee composition in the Senate and the knowledge spillover instrument, jointly. Column 1 reproduces the results for the top 1% income share. Column 2 uses the *Avgtop* measure, column 3 uses the top 10% income share, column 4 uses the overall Gini coefficient and column 5 uses the Gini coefficient for the bottom 99% of the income distribution to measure income inequality on the left-hand side of the regression equation. Columns 6 and 7 use two broader measures of inequality, namely the Atkinson

[47]Not all innovations are patented. Yet, as long as the share of patented innovation does not vary across states in a given year, this does not bias our estimation results. However, if this share is not constant overtime (for instance, because of regulatory changes), it does affect our measure of the increase in innovation. In particular, if the share of innovations that get patented has increased over time, then the increase in innovation is less than the measured increase in patents and innovation can only explain a smaller share of the rise of top income inequality. Kortum and Lerner (1999), however, do argue that the sharp increase in the number of patents in the 90's reflected a genuine increase in innovation and a shift towards more applied research instead of regulatory changes that would have made patenting easier.

[48]We chose to present results for the 3 year window citation variable but results are similar when using other measures of innovation quality.

Index with parameter 0.5 and the Theil index. The effect of innovativeness is non significant for the Theil Index neither is it for the Atkinson index.

Looking at column 2 of Table 6, we see that the effect of innovativeness on the share of income received by the top 10 to top 2% of the income distribution is significant but the coefficient is negative. Gini indexes (columns 4 and 5) show negative coefficients (although not significant for the overall Gini). Together, these results strongly suggest that the link between innovativeness and top income inequality is mainly driven by what happens at the very top of the income distribution, and specifically at the top 1% income share.[49]

4.5 Robustness checks

In this subsection we discuss the robustness of our regression results.

4.5.1 Choice of lags

One may question the interpretation of our positive and significant coefficients on the one year lagged innovation variable in our regressions. In particular, some may legitimately argue that one year after the application date is too short to have an impact on the inventor's income, especially since it takes on average two years between the application date and the date at which the patent is granted by the patent office.[50] Nevertheless we stick to the view that our positive and significant coefficients on the one year lagged innovation variable, already captures the effect of innovativeness on top income inequality. Empirical support for our view, is provided by two recent papers by Depalo and Di Addario (2014) and Bell et al (2015): Depalo and Di Addario (2014) find that inventors' wage peak around the time of the patent application, whereas Bell et al (2015) show that the earnings of inventors start increasing before the filing date of the patent application. More generally, patent applications are mostly organized and supervised by firms who start paying for the financing and management of the innovation right after (or even before) the application date as they anticipate the future profits from the patent. Also, firms may sell a product embedding an

[49]We also explored the data on the share of income held by the top 0.1% at the state level, directly provided to us by Mark Frank. These data are not as reliable as other measures of inequality and this is why we chose to concentrate on the top 1% in our analysis of the relationship between innovation and top income inequality. Yet, when running the same regression with the log of the top 0.1% income share as the left-hand side variable, the coefficient of innovation remains positive and significant, only slightly smaller than the coefficient of innovation on the log of the top 1% income share.

[50]For example, using Finnish individual data on patenting and wage income, Toivanen and Vaananen (2012) find an average lag of two years between patent application and patent grant, and they find an immediate jump in inventors' wages after patent grant.

innovation before the patent has been granted, thereby already appropriating some of the profits from the innovation.

Yet as a robustness check, we investigate what happens when longer innovation lags are included in the regression. More specifically, in our regression of the log of the top 1% income share on the log of the number of patents per capita (jointly instrumented by our two IVs) we allow the lag in innovativeness to vary from 1 to 5 years, and we lagged the instruments correspondingly. As seen in Table 7, the coefficient on innovation is always strongly significant and positive, regardless of which lag we are using. Moreover, the magnitude of the coefficient increases as we move from 1 to 3 year lag and then decreases before losing significance when the lag goes beyond 5 years—suggesting that, in line with the theory, the impact of a given innovation on top income inequality is temporary. We also checked the robustness of our results to using the granting date instead of the application date.[51]

Finally, we run an OLS regression to look at the effect on top 1% income share at date t when innovation is averaged over non-overlapping three year windows (that is, we count patents with application dates between $t-1$ and $t-3$). As seen in column 7 of Table 7, the coefficient on innovation is still highly significant and its magnitude is higher than when only patents filed at $t-1$ are included.[52]

4.5.2 The role of two specific sectors: finance and natural resources

When considering top income shares and other inequality measures on the one hand and innovativeness on the other hand, we abstracted from industry composition in the various states. However, two particular sectors deserve to be considered more closely: Finance and Natural resources.

The financial sector is overrepresented in the top 1% income share (even though most individuals in the top 1% do not work in the financial sector). More specifically, Guvenen, Kaplan and Song (2014) find that 18.2% of individuals in the top 1% work in the Finance, Insurance and Real Estate sector (versus 5.3% for the rest of the population), and that these individuals' income is particularly volatile. To make sure that our effects are not mainly driven by the financial sector, in the above regressions we already controlled for the share of the financial sector in state GDP.

Here, we perform additional tests. First, we add the average employee compensation in

[51] We find a regression coefficient which is a little higher than before, and closer to the 3 and 4 year lag coefficients in the regressions on patent application. This is in turn consistent with the time lag between patent application and patent grant being of about two years (not shown here).

[52] This result is not surprising: first, we include patents that have been filed before $t-1$ and can still have an effect at t; second, the averaging reduces the scope for bias due to measurement errors in innovativeness.

the financial sector as a control to capture any direct effect an increase in financial sector's employee compensation might have on the top 1% income share. Second, we exclude states in which financial activities account for a large fraction of GDP. We selected four such states: New York, Connecticut, Delaware and South Dakota.

Third, financial innovations themselves might directly increase rents and therefore the top 1% income share. To account for this latter channel, we subtract patents belonging to the class 705: "Financial, Business Practice" related to financial activities in order to exclude innovations in the financial sector.

The IV regressions of the top 1% income share on innovativeness (measured by the number of citations per capita within a 3 year window, but this is also true with other measure of innovation) corresponding to these three robustness tests are presented in Table 8, respectively in columns 1, 2 and 3.[53] In each case, the effect of innovativeness on the top 1% income share is significant and positive, showing very stable values when moving from one specification to another.

Another potential issue related to finance is that financial development should impact both innovation (by providing easier access to credit to potential innovators) and income inequality at the top (by boosting high wages). Our IV strategy should in principle address omitted variable issues including this one, yet here we construct a variable specifically designed to directly capture this channel. For each US state, we divide patent application in that state into 16 NAICS categories and use the external financial dependence index computed by Kneer (2013) and averaged over the period 1980-1989. External financial dependence is defined as the ratio of capital expenditure minus cash flow divided by capital expenditure (see Rajan and Zingales, 1998). We multiply the number of patents in each NAICS sector in that state by that index and then divide by the total number of patent to compute a variable representing the level of financial dependence of innovation. This variable (denoted EFD in Table 8) should capture a variation in innovativeness at state-level driven by a sector that is highly dependent on external finance. Results for regressing the top 1% income share on the number of citations per capita within a 3 year window when controlling for EFD are presented in column 4. We see that the effect of innovativeness remains significant, even if the coefficient is slightly lower than the corresponding coefficient when we do not control for EFD in Tables 5 and 6.

Natural resources and oil extraction represent a large share of GDP in certain states (In Wyoming, West Virginia and particularly Alaska, oil extraction activities account for almost 30% of total GDP in 2009), so that in these states the top 1% income share is likely to be

[53] In this table we jointly instrument by the appropriation committee and knowledge spillover variables.

affected by these sectors which are quite volatile (oil extraction is highly sensitive to energy prices fluctuation). To deal with this concern, we control for the share of natural resources in GDP. In addition, we first add the share of oil extraction related activities in state GDP as a control variable; and second, we remove patents from class 208 (Mineral oils: process and production) and 196 (Mineral oils: Apparatus). Results are presented in columns 5 and 6 of Table 8. Here again, our results remain significant.[54]

4.5.3 Looking at industry composition

In this subsection, we check that our results are robust to controlling for sectors' size. First, we use the previous decomposition into 16 NAICS categories to remove patents related to the NAICS numbered 334: "Computer and Electronic Products", to deal with the concern that the effect of innovativeness on top income inequality might be concentrated in the fast-growing computer industry. Similarly, we remove patents from the pharmaceutical sector (NAICS 3254) and from the electrical equipment sector (NAICS 335). In each case, we conduct an IV panel regression combining our two instruments. The results remain unchanged with the coefficient of the number of patents per capita on top income inequality remaining quite stable across specifications. Then, in our regressions we add controls for the logarithm of the *GDP* of these three NAICS. Innovation remains still positively and significantly correlated with the top 1% income share.

In addition, we used the COMTRADE database to look at the extent to which our effect of innovation on top income inequality is driven more by more exporting sectors. Over the period from 1975 to 2010, we identified three sectors that are particularly export-intensive: Transportation, Machinery and Electrical Machinery. When we regress the top 1% income share on patenting from those three sectors versus on patenting from other sectors, and using our two instruments jointly, we obtain a higher coefficient when restricting attention to the three most exporting sectors: 0.239 versus 0.165 for the other sectors. This result is in line with the notion that larger markets increase the reward from innovation, thereby increasing the effect of innovation on top income inequality. All these results are available in appendix, Table 16.

4.5.4 Accounting for changes in top tax rates

Taxation is likely to affect both innovation incentives and the 1% income share. In particular, high top marginal income tax rates may reduce efforts by top earners, divert their pay from wages to perks, and reduce their incentives to bargain for higher wages (see, in particular,

[54]We obtain similar results when using other measures of innovativeness.

Piketty, Saez and Stantcheva, 2014). In this subsection, we address this concern more directly, even though our IV strategy is meant to address such omitted variable bias issues.

More specifically, we use data from the NBER TAXSIM website.[55] This database provides information on marginal tax rates for various levels of incomes ($10000, $25000, $50000, $75000 and $100000 yearly incomes) and for labor, capital and interest incomes from 1977 onward. We use the state marginal labor income tax rate for individuals earning $100000 per year as an additional control when regressing the top 1% income share on innovativeness. The results are displayed in Column (7) of Table 8: the effect of innovativeness on the top 1% income share remains positive and significant.[56]

4.5.5 Controlling for agglomeration effects

One may wonder whether our results do not reflect potential agglomeration effects: for example, suppose that some exogenous investment taking place in one particular location (think of the Silicon Valley), makes that location become more attractive to skilled/talented individuals from other parts of the US. Then the resulting increased agglomeration of high-skill individuals in that location, should result in both, a higher share in the top 1% income share and in an increase in innovation in the corresponding US state, but without the former necessarily resulting from the latter.

Note first that our two instruments are meant to take care of all potential omitted variable problems. Moreover, to address the agglomeration objection head on, we can directly control for agglomeration in any state i at any date t as follows: in state i in year t, we look at the three most innovative technological classes from our patent dataset. We then count the number of patenting firms in these technology classes in that state in that year. The log of that number is our new control variable $Agglo_{it}$ which is meant to capture potential agglomeration effects in state i in year t.

Running all our previous regressions with these additional control variables $Agglo_{it}$ turns out not to affect our results as seen in the corresponding regression table in the Appendix (see table 17). Moreover, the same is true when we control for the number of firms in the single most innovative class, or for the number of firms in the two most innovative classes.[57]

[55] http://users.nber.org/ taxsim/state-tax-tables/

[56] Results are similar when other marginal top tax rates are used as controls.

[57] An alternative approach here would be to simply include state specific time trends as additional controls in our regressions. We chose not to present results that include state-specific time trends as these trends will depend on post-innovation inequality. As noted in Wolfers (2006), among others, such trends tend to confound measures of impact in cross-state panel regressions making identification difficult to argue. Instead, to show robustness of our results to differences across states in pre-innovation trends, we considered including specific controls. In particular, to account for potential agglomeration effects we controlled for the number

4.6 Star inventors and top income shares

Some innovators are more highly talented than others and therefore more likely to move up to the top 1% income bracket themselves or help the top management in their firms enter the top 1% (in terms of our model such innovators would generate innovations with size greater than η_H, thereby further increasing the share of entrepreneurial income). To assess the influence of the most talented innovators more directly, we calculate the number of "star inventors" in each state each year. Following Acemoglu et al. (2014), we define a star inventor by looking at the adjusted number of citations to her patents in a given year.[58] We then rank inventors according to two criteria: the maximum and the average number of citations they received.[59] Each inventor is then associated with a score for each year, and a star inventor is defined as one that made it to the top 5% according to that score.

The USPTO database, combined with the work of Lai et al. (2013), allows us to look at inventors for each patents granted from 1975 to 2010. We aggregate this measure at the state level by computing the number of star inventors per capita in each state and each year. If a star inventor has different patents in different states, each state is attributed its corresponding fraction of the inventor's citations. Then we use our instruments to conduct a 2SLS IV regression. Results are presented in Table 9. Columns 1 to 3 use the maximum number of citations as a criterium to detect star inventors while columns 4 to 6 use the mean number of citations. In every case, the results show that an increase in the number of star inventors in a given state has a positive and significant effect on the top 1% income share.

5 Social mobility, lobbying, and entrant versus incumbent innovation

In this section we extend our core analysis in three directions: first, moving from cross-state to CZ-level analysis, we consider the relationship between innovativeness and social mobility;

of firms in the most innovative sectors in each state each year. However, we note that our results are largely preserved when adding state-specific trends. More specifically, adding state-specific time trends: (i) does not alter our OLS results as long as we measure innovation by our various citation measures (the regression coefficients are only slightly lower than before) are concerned; (ii) eliminates the effect of patent count on top income inequality. Our IV results remain roughly the same when innovation is measured by our citation-based measures, although the instruments are somewhat weaker (with lower F statistics). These regressions are available upon request from the authors.

[58]Similar definitions of superstars are also used in Akcigit, Baslandze and Stantcheva (2015) who study the international mobility of superstar inventors in response to top tax rate changes

[59]The number of citations has been corrected so as to compare between inventors across various technological fields.

second, we distinguish between entrant and incumbent innovation; finally, we focus on a particular source of entry barriers, namely lobbying activities across US states, and we look at how lobbying intensity affects the impact of innovativeness on top incomes and on social mobility.

5.1 From cross-state to CZ-level analysis

Panel data on social mobility in the United States are not (yet) available. Therefore, to study the impact of innovativeness on social mobility without reducing the number of observations too much, we move from cross-state to cross-commuting zones (CZ) analysis and use the measures of social mobility from Chetty et al (2014). A commuting zone (CZ) is a group of neighboring counties that share the same commuting pattern. There are 741 commuting zones which cover the whole territory of the United States. Some CZs are in rural areas whereas others are in urban areas (large cities and their surroundings). At the CZ level, we do not have data on top income shares for the whole population. However, Chetty et al (2015) use the 2000 census to provide estimates for the top 1% share as well as for the Gini index for a sample of adults at CZ and MSA level. Using that information, we compute cross-sectional measures of inequality as an average between 1996 and 2000. If we look at urban CZs, the three largest top 1% income shares are in New York (23.6%), San Jose (26.4%) and San Francisco (29.1%), all of which are highly innovative areas.

To associate a patent to a CZ location, we rely on Lai *et al.* (2013) to complete the USPTO database as we did when looking at star scientists. This enables us to associate each inventor with her address and her zipcode which can be linked up to a county, and ultimately to a commuting zone. Finally, we aggregate county level data on GDP and population from the BEA to compute GDP per capita and population growth. All other data are taken from Chetty *et al.* (2015).

5.2 The effect of innovation on social mobility

Having moved from cross-state to cross-CZ analysis allows us to look at how innovativeness affects social mobility, using the various measures of social mobility in Chetty *et al.* (2015) combined with our local measures of innovation and with the various controls mentioned above. There, absolute upward mobility is defined as the expected percentile or “rank” (from 0 to 100) for a child whose parents belonged to some P percentile of the income distribution. Percentiles are computed from the national income distribution. The ranks are computed over the period 2011-2012 when the child is aged around 30 whereas the percentile

P of parents income is calculated over the period between 1996 and 2000 when the child was aged around 15. In addition, Chetty *et al.* (2015) provide transition matrices by CZ and by quintile: in other words, one can estimate the probability for a child to reach quintile i of the national income distribution when the parents belonged to quintile j for all (i, j). Once again, the intensity of innovativeness in each CZ is measured by the average number of patents per capita, but this time, we take the averages over the period 2006-2010.

One potential concern with these data for our purpose, is that social mobility is based on the location of the parents not the children, and therefore the data do not account for children who move to and then innovate in a different location from that of their parents. However, if anything this should bias our results downwards: if many individuals migrate out of a specific CZ to innovate in San Francisco or New York, this CZ will exhibit high social mobility but low innovativeness.

We thus conduct the following regression:

$$log(Mob_i) = A + \beta_1 log(innov_i) + \beta_2 X_i + \varepsilon_i,$$

where Mob is our measure of upward social mobility, and $innov$ is our Measure of innovation (the number of patents per capita at the CZ level). We cluster standard errors by state. Table 11 presents our results for this cross-section OLS regression. We add our regular set of controls including the share of the manufacturing sector, the labor force participation rate taken in 1996-2000, college graduation rate and the local expenditures in public school per student during the same period. Columns 1 and 4 look at the effect of innovativeness on upward mobility when parent income belongs to the 25th percentile. The effect of innovativeness is positive and significant. Columns 2, 3, 5 and 6 show the effects of innovativeness on the probability for a child to belong to the highest quintile in income distribution at age 30 when her parent belonged to a lower quintile. The lower the quintile to which parents belonged, the more positive and significant is the correlation between innovativeness and upward mobility.[60] Not surprisingly, school expenditures, colleges per capita and participation rate also play a positive role in explaining upward social mobility, while the size of the manufacturing sector is negatively correlated. Finally, column 7 shows the overall effect of innovativeness on upward mobility measured by the probability to reach the highest quintile when parent belonged to any lower quintile. Here again, the correlation is positive.

One concern is worth mentioning here: in some CZs, the size of the top quintile is very

[60] If we continue with quintiles 3 and 4, the effect of innovativeness on social mobility is still significant for quintile 3 (but only when college per capita and manufacturing share are not included) and negative and not significant for quintile 4.

small, reflecting the fact that it is almost impossible to reach this quintile while staying in this CZ. This case often occurs in rural areas: for example, in Greenville, a CZ in Mississippi, only 7.5% of children in 2011-2012 (when they are 30) belong to the highest quintile in the national income distribution. To address this concern, we conduct the same regressions as above but we remove CZs where the top quintile has a size below 10% and below 15% (this exclude respectively 7 and 100 CZs). All our results remain consistent with columns 1 to 6 of the previous regressions.[61] In fact, the results are even stronger, with the coefficient of innovation being now always significant at the 5% level.

All the results presented in this section are consistent with the prediction of our model that innovativeness increases mobility at the top. Yet, we should bear in mind that these are just cross-sectional OLS correlations, and this remark holds for all other CZ level regressions in this section.

5.3 Entrant versus incumbent innovation

Our empirical results have highlighted the positive effects of innovativeness on top income inequality and also on social mobility. Now, our model suggests that the effect of innovativeness on social mobility should operate mainly through entrant innovation, meanwhile the effect on top income inequality operates through both types of innovation. In order to distinguish between incumbent and entrant innovation in our data, we declare a patent to be a "entrant patent" if the time lag between its application date and the first patent application date of the same assignee amounts to less than 3 years.[62] We then aggregate the number of "entrant patents" as well as the number of "incumbent patents" at the state level from 1979 to 2010[63] and at the CZ level by averaging between 2006 and 2010.

We first focus on the effect of entrant innovation on social mobility. We thus conduct the same regression as in the previous section at the cross CZ level but considering separately entrant innovation and incumbent innovation on the right hand side of the regression

[61] This result is confirmed by performing the same regression on the whole sample of CZs but adding an interaction term between the number of patents per capita and a dummy equal to one if the CZ has a top quintile of size higher than 15% of total CZ population. The coefficient for this interaction term is positive and significant.

[62] We checked the robustness of our results to using a 5-year lag instead of a 3-year lag threshold to define entrant versus incumbent innovation. Here we only focus on patents issued by firms and we have removed patents from public research institute or independent inventors. Results are also robust when independent inventors are included.

[63] We start in 1979 to reduce the risk of wrongly considering a patent to be an "entrant" patent just because of the truncation issue at the beginning of the time period. In addition, we consider every patent from the USPTO database, including those with application year before 1975 (but which were granted after 1975).

equation. Table 12 presents our results. Columns 1 to 3 regress our three measures of social mobility on the number of "entrant patents" per capita, whereas columns 4 to 6 regress the three measures of social mobility on the number of "incumbent patents". The positive and significant coefficients in the first three columns, as compared to columns 4 to 6, suggest that the positive effect of innovativeness on social mobility is mainly driven by new entrants. This conjecture is confirmed by the horse race regression in column 7 in which both entrant innovation and incumbent innovation are included as right-hand side variables. There, we clearly see that all the effect of innovation on social mobility is associated with entrant innovation.

Next, we look at the effect of entrants' innovation on top income inequality, making full use of our panel data at the cross state level. Following our definition of entrant innovation, 17% of patent applications from 1979 to 2010 can be considered "entrant" (this number increases up to 23.7% when we use the 5-year lag threshold to define entrant versus incumbent innovation). These "entrant" patents have more citations than incumbent patents, for example in 1980, entrant patents have 11.4 citations on average while incumbent only have 9.5 citations, confirming the intuitive idea that entrant patents correspond to more radical innovations (see Akcigit and Kerr, 2010).

Table 13 presents the results from the OLS panel regression of the top 1% income share over two measures of innovativeness (number of patents per capita and number of citations per capita), restricting attention respectively to entrant patents (columns 1 and 4) and to incumbent patents (columns 2 and 5).[64] The coefficients on innovativeness are always positive and significant when innovativeness refers to either entrant innovation or to incumbent innovation, yet with a smaller coefficient for the latter. In addition, columns 3 and 6 regress the top 1% income share on both incumbent and entrant innovation, confirming that both types of innovations show significant coefficients,[65] in line with what the theory predicts.

5.4 Lobbying as a dampening factor

To the extent that lobbying activities help incumbents prevent or delay new entry, our conjecture is that places with higher lobbying intensity should also be places where innovativeness has lower effects on the top income share and on social mobility.

[64] We do not show the IV regressions. What we obtain is that: (i) the IV regression using both instruments works for incumbent innovation; (ii) the IV regression using the senate appropriation committee IV works for entrant innovation if we add one year lag to the instrument; (iii) the knowledge spillovers instrument does not work for entrant innovation. Overall, this is not too surprising: knowledge spillovers and federal subsidies take time to be effective and thus are more likely to affect established firms than entrants.

[65] The difference between the two coefficients is not statistically significant.

Measuring lobbying expenditures at state or at CZ level is not straightforward. In particular, the OpenSecrets project[66] provides sector specific lobbying expenditure only at national level, not at the state and CZ levels. In order to measure lobbying intensity at the state level, we construct for each state a Bartik variable, as the weighted average of lobbying expenditures in the different sectors (2 digits NAICS sectors), with weights corresponding to sector shares in the state's total employment from the US Census Bureau.

More precisely, we want to compute $Lob(i,.)$ the lobbying expenditure in state i, knowing only the national lobbying expenditure $Lob(.,k)$ by sector k. We then define the lobbying intensity by sector k in state i as:

$$Lob(i,k) = \frac{emp(i,k)}{\sum_{j=1}^{I} emp(j,k)} Lob(.,k),$$

where $emp(i,k)$ denotes industry k's share of employment in state i (where $1 \leq k \leq K$ and $1 \leq i \leq I$).

From this we compute the aggregate lobbying intensity in state i as:

$$Lob(i,.) = \frac{\sum_{k=1}^{K} emp(i,k) Lob(i,k)}{\sum_{k=1}^{K} emp(i,k)}$$

At the CZ level, there is no sectoral employment composition, however, such data exist at the cross MSA level for the manufacturing sector (we use a 3 digits NAICS level) from the Longitudinal Employer Household Dynamics dataset. We therefore move the analysis from CZ to MSA at this point and compute similar Bartik measures of lobbying intensity at that level.

We define states with higher than median lobbying intensity as high lobbying intensity states and create a dummy equal to one whenever a state belongs to that group.[67] We then interact this dummy with the logarithm of the number of patents per capita. Columns 1 and 3 of Table 14 shows the results respectively for the OLS (column 1) and for the IV (column 3) regressions with both instruments of the top 1% income share on the total number of citations per capita (in log and lagged) and the interaction term between the dummy variable for high

[66] https://www.opensecrets.org/lobby/list_indus.php

[67] These 23 states are: AL, AR, IA, ID, IN, KS, KY, ME, MI, MO, MS, NC, NE, NH, OH, OK, RI, SC, SD, TN, VT, WI and WV.

lobbying intensity and the log of the number of citations per capita. The results shows that if the overall effect of innovativeness on the top 1% income share is always significant and positive, the effect is less strong in states with higher lobbying intensity. In addition, in a horse-race regression (column 2) where we split the innovativeness variable between entrant and incumbent innovation, we see that lobbying dampens the impact of entrant innovations on the top 1% income share while it has no effect on the impact of incumbent innovation on the top 1% income share, as predicted by the model.

We now look at how lobbying intensity impacts on the effect of innovativeness on social mobility, using cross-MSA data. As explained above, we aggregated patent applications by zipcode and then by MSA and used mobility data from Chetty et al. (2014) who only provide absolute mobility data and no transition matrix for MSAs. Our regular control variables (GDP per capita, population growth, share of financial sector and government size) have been found in the BEA and averaged over the period 2006-2010. Overall, we are left with 352 MSAs which can be separated in two groups of equal size, respectively with high and low lobbying activities. Columns 4 and 5 of Table 14 show the effect of innovation as measured by the number of entrant patents per capita (in log) on the logarithm of absolute upward mobility. Column 4 focuses on MSAs above median in terms of lobbying activities and column 5 on other MSAs. Similarly, columns 6 and 7 look at the effect of the number of incumbent patents per capita on absolute upward mobility. We see that the effect of entrant innovation on social mobility is positive and significant only for MSAs that are below median in terms of lobbying intensity. In addition, incumbent innovation has no effect on social mobility, whether we look at MSAs above or below the median in terms of lobbying intensity. These results confirm the idea that lobbying dampens the impact of innovativeness on social mobility by reducing the effect of entrant innovation. To sum up, in line with our model, lobbying reduces the impact of innovativeness on social mobility and its impact on the top 1% income share.[68]

6 Conclusion

In this paper we have shown that top income inequality is at least partly driven by innovation. We first showed positive and significant correlations between measures of innovativeness on

[68]In line with these findings, in another regression which we are not showing here we find that venture capital -which presumably fosters entrant innovation- enhances the effect of innovativeness on top income inequality: using data on the total number of deal by states from the National Venture Capital Yearbook 2014, we find that in state where venture capital intensity is higher, innovation has a more positive effect on top income, but only for entrants.

the one hand, and top income inequality on the other hand. Moreover, our instrumentation at cross-state level suggested that these correlations at least partly reflect a causality from innovativeness to top income shares. Finally, we showed that innovation does not affect broader measures of inequality and that it is positively associated with social mobility.

These findings suggest interesting avenues for further research on (innovation-led) growth, inequality and social mobility. First, In our IV regressions we are only directly investigating the causal impact of innovation on top income inequality, not the reverse. However, the comparison between our OLS and our IV results suggests that there are key components of top 1% inequality that should have a negative impact on innovation. Identifying these components is certainly an important avenue for future research.

Another related extension would be to explore policy implications. In particular, how do we factor in innovation in tax policy design, and how should we combine tax policy with other policy instruments (competition and entry policy, patent policy, R&D subsidies,...) to achieve more inclusive growth?

Another extension would be to look at the effect of innovation on top income inequality in cross-country panel data. Preliminary OLS regressions show a positive and significant correlation between our innovativeness measures and top 1% income share in cross-country panel.

A fourth extension is to explore the relationship between innovation, top income inequality and social mobility using individual data on revenues and patenting.[69] Note however that while such studies based on the matching between individual patenting data and individual fiscal data, allows us to more directly identify the effect of innovation on upward income mobility for inventors, unlike our analysis in this paper they do not account for the aggregate effect of innovation on top income inequality: this effect goes well beyond the inventor as it involves all those who benefit from the inventor's innovation, starting with the firm that employs the inventor.

A fifth extension would be to look at innovation beyond patenting. As a first step in that direction, we looked at the relationship between top income inequality and frontier versus non-frontier growth, where frontier growth is defined as growth in states where labor productivity is closer than the median to the productivity in the most productive US state that year. Preliminary cross-state panel OLS regressions show a positive and significant correlation between top income inequality and frontier growth, but a negative correlation between top income inequality and non-frontier growth. Overall, these two findings are consistent with the view that the positive correlation between top inequality and growth, if

[69] In Aghion-Akcigit-Toivanen (2015) we are conducting such a study using Finnish individual data over the period 1990-2000. See also Toivanen and Vaananen (2012) and Bell et al (2015).

any, is driven by innovation-led growth.

Finally, our results on the impact of lobbying suggests that the relationship between innovativeness and income inequality depends upon institutional factors which vary across countries. Further research should thus look deeper into how institutions affect the relationship between top income inequality and innovation. These and other extensions of the analysis in this paper are left for future research.

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7 Tables

Variable Names	**Description**
	Measure of inequality
top1	Share of income own by the richest 1% (on a scale of 0 to 100).
top10	Share of income own by the richest 10% (on a scale of 0 to 100).
Gini	Gini index of inequality.
G99	Gini index restricted to the bottom 99% of income distribution.
Theil	Theil index of inequality.
Atkin	Atkinson index of inequality.
	Measure of innovation
patent_pc	Number of patents granted by the USPTO per thousand of people.
3 (resp 4 and 5) YWindow	Total number of citation received no longer than 3 (resp 4 and 5)years after per thousand of inhabitant. application.
Share5	Total number of patent among the 5% most cited in a given application per thousand of inhabitant. year.
Citations	Total number of citations made to patents per thousand of inhabitants.
Renew	Number of patents that have been renewed at least once per thousand of inhabitants.
	Measure of social mobility
AM25	Expected percentile of a child at 30 whose parents belonged to the 25^{th} percentile of income distribution in 2000.
AM50	Expected percentile of a child at 30 whose parents belonged to the 50^{th} percentile of income distribution in 2000.
P5-i	Probability for a child at 30 to belong to the 5^{th} quintile of income distribution if parent belonged to the i^{th} quintile, $i \in \{1, 2\}$.
P5	Probability for a child at 30 to belong to the 5^{th} quintile of income distribution if parent belonged to lower quintiles.
	Control variables
Gdppc	Real GDP per capita in US $ (in log).
Popgrowth	Growth of total population.
Sharefinance	GDP of financial sector divided by total population (in log).
Outputgap	Output gap.
Gvtsize	GDP of government sector divided by total population (in log).
Highways	Federal expenditure on highways divided by total population (in log).
Military	GDP of public military sector divided by total population (in log).
Spill_Gdppc	Weighted value of other states GDP per capita at t-1 (in log).
	Additional control variables at the CZ level
Participation Rate	Labor Share participation rate.
College per capita	College graduation rate.
School Expenditure	Average expenditures per student in public schools (in log).
Employment Manuf	Share of employed persons 16 and older working in manufacturing.

Table 1: Description of relevant variables used in regressions. Additional variables may be used in specific analysis, in this case they will be explained in the corresponding table description.

Measure of Inequality Innovation	**(1)** Top 1% patent_pc	**(2)** Top 1% patent_pc	**(3)** Top 1% patent_pc	**(4)** Top 1% patent_pc
Innovation	0.021*	0.026**	0.028**	0.027*
	(2.00)	(2.06)	(2.03)	(1.89)
Gdppc		-0.071	-0.101	-0.060
		(-1.16)	(-1.29)	(-0.52)
Popgrowth		0.011	0.333	0.280
		(0.01)	(0.43)	(0.37)
Sharefinance			0.016	0.013
			(0.72)	(0.57)
Outputgap			-1.986	-1.954
			(-1.35)	(-1.37)
Gvtsize				-0.070
				(-0.76)
R^2	0.919	0.919	0.920	0.920
N	1785	1785	1785	1785

Table 2: Effect of the number of patents per capita (in log and lagged) on the logarithm of the top 1% income share. Time span: 1975-2010. Panel data OLS regressions. State-fixed effect and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality Innovation	(1) Top 1% 3YWindow	(2) Top 1% 4YWindow	(3) Top 1 % 5YWindow	(4) Top 1% Citations	(5) Top 1% Share5	(6) Top 1% Renew
Innovation	0.032***	0.042***	0.041***	0.048***	0.022***	0.025***
	(3.72)	(4.58)	(4.24)	(5.78)	(4.23)	(2.71)
Gdppc	-0.089	-0.068	-0.055	-0.091*	-0.061	-0.130*
	(-1.55)	(-1.21)	(-0.94)	(-1.66)	(-1.13)	(-1.90)
Popgrowth	0.138	0.024	-0.174	0.068	0.028	0.984
	(0.22)	(0.04)	(-0.24)	(0.10)	(0.04)	(1.30)
Sharefinance	0.022*	0.024*	0.026*	0.024*	0.021	0.015
	(1.67)	(1.74)	(1.76)	(1.87)	(1.58)	(1.13)
Outputgap	-1.826	-2.302	-2.143	-2.115	-2.128	-3.265*
	(-1.27)	(-1.64)	(-1.46)	(-1.53)	(-1.53)	(-1.95)
Gvtsize	-0.085**	-0.109**	-0.139***	-0.090**	-0.099**	-0.065
	(-2.00)	(-2.51)	(-3.09)	(-2.16)	(-2.34)	(-1.28)
R^2	0.921	0.916	0.908	0.921	0.921	0.885
N	1632	1581	1530	1632	1632	1435

Table 3: Effect of different measures of the quality of innovation (in log and lagged) on the logarithm of the top 1% income share. Time span: 1975-2007 for column (1), 1975-2006 for column (2), 1975-2005 for column (3), 1976-2007 for column (3), 1976-2007 for column (5) and 1982-2007 for column (6). Panel data OLS regressions. State-fixed effect and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality Innovation	**(1)** Top 1% patent_pc	**(2)** Top 1% patent_pc	**(3)** Top 1 % patent_pc	**(4)** Top 1% 3YWindow	**(5)** Top 1% 3YWindow	**(6)** Top 1% 3YWindow
Innovation	0.166** (2.12)	0.183** (2.04)	0.177** (1.99)	0.145** (2.23)	0.139** (2.32)	0.160** (2.01)
Gdppc	-0.122 (-1.52)	-0.135 (-1.61)	-0.130 (-1.59)	-0.153 (-1.63)	-0.147* (-1.76)	-0.168* (-1.67)
Popgrowth	0.728 (1.07)	0.778 (1.15)	0.758 (1.10)	0.735 (0.99)	0.703 (0.97)	0.813 (1.03)
Sharefinance	0.022 (1.52)	0.024 (1.57)	0.023 (1.59)	0.041** (2.08)	0.039** (2.15)	0.044** (2.12)
Outputgap	-2.408* (-1.70)	-2.451* (-1.74)	-2.434* (-1.68)	-1.947 (-1.23)	-1.942 (-1.24)	-1.961 (-1.21)
Gvtsize	-0.100** (-2.20)	-0.098** (-2.12)	-0.099** (-2.20)	-0.084 (-1.44)	-0.087 (-1.58)	-0.076 (-1.27)
Highways	0.028*** (3.15)	0.029*** (3.11)	0.029*** (2.98)	0.027*** (3.02)	0.026*** (3.09)	0.028*** (2.80)
Military	0.008** (2.03)	0.008** (2.06)	0.008* (1.95)	0.011** (2.43)	0.010** (2.44)	0.011** (2.28)
Lag of instrument	2 years	1 year	3 years	2 years	1 year	3 years
R^2	0.913	0.910	0.912	0.913	0.914	0.911
1^{st} stage F-stat	27.10	21.98	21.54	18.84	21.78	13.92
N	1748	1748	1748	1598	1598	1598

Table 4: Effect of two measures of the quality of innovation (in log and lagged) on the logarithm of the top 1% income share. Time span: 1975-2010 for columns (1) to (3) and 1975-2007 for others. Panel data IV (2 SLS) regressions with the number of seats occupied at the appropriation committee in the Senate as an instrument for inovativeness. State-fixed effect and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality Innovation	**(1)** Top 1% patent_pc	**(2)** Top 1% 3YWindow	**(3)** Top 1 % 4YWindow	**(4)** Top 1% 5YWindow	**(5)** Top 1% Citations	**(6)** Top 1% Share5
Innovation	0.162**	0.124**	0.136***	0.147***	0.201***	0.297**
	(2.24)	(2.53)	(2.59)	(2.69)	(2.81)	(2.14)
Gdppc	-0.169*	-0.206**	-0.176*	-0.184*	-0.245**	-0.280*
	(-1.80)	(-2.00)	(-1.79)	(-1.74)	(-2.23)	(-1.80)
Popgrowth	0.773	0.653	0.480	0.365	0.285	0.812
	(1.12)	(0.92)	(0.67)	(0.46)	(0.42)	(0.74)
Sharefinance	0.026*	0.043**	0.043**	0.050**	0.054***	0.092**
	(1.82)	(2.46)	(2.39)	(2.49)	(2.74)	(2.21)
Outputgap	-2.427*	-2.000	-2.738*	-2.265	-2.105	-2.772
	(-1.68)	(-1.27)	(-1.78)	(-1.44)	(-1.47)	(-1.31)
Gvtsize	-0.038	-0.015	-0.035	-0.058	-0.032	0.007
	(-0.79)	(-0.24)	(-0.54)	(-0.84)	(-0.55)	(0.08)
Spill_Gdppc	0.050	0.307	0.436	0.413	0.092	0.356
	(0.11)	(0.61)	(0.86)	(0.83)	(0.20)	(0.45)
R^2	0.909	0.911	0.907	0.897	0.903	0.740
1^{st} stage F-stat	20.93	25.49	23.78	22.63	18.11	4.93
N	1785	1632	1581	1530	1632	1559

Table 5: Effect of different measures of the quality of innovation (in log and lagged) on the logarithm of the top 1% income share. Time span: 1976-2010 for column (1), 1976-2007 for column (2), 1976-2006 for column (6), 1976-2005 for column (4), 1976-2007 for column (5) and 1976-2007 for column (6). Panel data IV (2 SLS) regressions with the the spillover at time t-1 used as an instrument for inovativeness. States-fixed effect and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality Innovation	(1) Top 1% 3YWindow	(2) Avgtop 3YWindow	(3) Top 10 % 3YWindow	(4) Overall Gini 3YWindow	(5) G99 3YWindow	(6) Atkin 3YWindow	(7) Theil 3YWindow
Innovation	0.145***	-0.033*	0.010	-0.013	-0.030**	0.025	0.028
	(3.21)	(-1.65)	(0.89)	(-1.03)	(-2.25)	(1.57)	(0.92)
Gdppc	-0.171*	0.087**	0.049**	-0.031	-0.040	0.113***	0.361***
	(-1.81)	(2.39)	(1.97)	(-1.24)	(-1.45)	(3.15)	(4.86)
Popgrowth	0.941	-0.524*	0.074	-0.411**	-0.676***	0.401	2.393***
	(1.30)	(-1.95)	(0.41)	(-2.42)	(-3.53)	(1.45)	(3.94)
Sharefinance	0.037**	-0.008	0.007	-0.001	-0.009	0.019**	0.005
	(2.24)	(-0.91)	(1.28)	(-0.16)	(-1.37)	(2.26)	(0.34)
Outputgap	-3.674**	-0.419	-0.508	0.076	0.193	0.144	0.218
	(-2.28)	(-0.82)	(-1.48)	(0.20)	(0.44)	(0.26)	(0.20)
Gvtsize	-0.049	-0.041	-0.061***	0.036*	0.066***	-0.090***	-0.234***
	(-0.83)	(-1.45)	(-3.38)	(1.95)	(3.01)	(-3.38)	(-4.37)
Highways	0.024***	-0.006	0.003	0.009***	0.010***	0.001	-0.004
	(2.79)	(-1.49)	(1.13)	(3.01)	(2.96)	(0.18)	(-0.48)
Military	0.012**	-0.002	0.001	-0.002	-0.003*	-0.001	0.002
	(2.37)	(-1.26)	(1.22)	(-1.33)	(-1.87)	(-0.41)	(0.54)
Spill_Gdppc	0.616	0.671***	0.354**	0.607***	0.732***	0.272	-0.261
	(1.18)	(3.08)	(2.21)	(3.68)	(3.96)	(1.25)	(-0.61)
R^2	0.908	0.534	0.950	0.875	0.734	0.932	0.928
1^{st} stage F-stat	21.03	21.03	21.03	21.03	21.03	21.03	21.03
N	1598	1598	1598	1598	1598	1598	1598

Table 6: Effect of the 3 year window citation number (in log and lagged) on the logarithm of different measures of inequality. Column (1) uses the top 1% income share, column (2) uses the average percentile between 2 and 10, column (3) uses the top 10% income share, column (4) uses the overall Gini coefficient and column (5) the bottom 99% Gini coefficient. Time span: 1975-2007. Panel data IV regressions with both instruments (spillover and appropriation committee composition). State-fixed effect and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	top 1%	top1%	top 1%	top1%	top 1%	top1%
Innovation	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc
Lag of innovativeness	1 year	2 years	3 years	4 years	5 years	Average 3 year
Innovation	0.184***	0.194***	0.216***	0.207***	0.199***	0.032***
	(3.37)	(3.00)	(3.10)	(2.97)	(2.91)	(2.05)
Gdppc	-0.143*	-0.160*	-0.202**	-0.226***	-0.245***	-0.189*
	(-1.81)	(-1.92)	(-2.44)	(-2.60)	(-2.67)	(-1.93)
Popgrowth	0.792	0.908	1.121	1.396	1.839**	0.060
	(1.16)	(1.18)	(1.39)	(1.64)	(2.09)	(0.07)
Sharefinance	0.024*	0.027*	0.030*	0.028*	0.024	0.027
	(1.70)	(1.86)	(1.94)	(1.78)	(1.53)	(1.38)
Outputgap	-2.520*	-2.740*	-3.025**	-3.708**	-4.507***	-0.791
	(-1.76)	(-1.78)	(-2.03)	(-2.32)	(-2.70)	(-0.27)
Gvtsize	-0.094**	-0.064	-0.029	-0.009	-0.011	0.011
	(-2.00)	(-1.30)	(-0.53)	(-0.16)	(-0.19)	(0.16)
Highways	0.029***	0.025***	0.023**	0.017*	0.015	
	(3.33)	(2.67)	(2.44)	(1.75)	(1.63)	
Military	0.009**	0.009**	0.010**	0.009**	0.007	
	(2.08)	(2.20)	(2.28)	(2.06)	(1.50)	
Spill_Gdppc	0.220	-0.039	-0.018	0.057	0.199	
	(0.48)	(-0.09)	(-0.04)	(0.11)	(0.38)	
R^2	0.910	0.902	0.891	0.883	0.872	0.918
1^{st} stage F-stat	25.48	20.59	18.12	17.59	20.10	-
N	1748	1698	1648	1598	1548	561

Table 7: Effect of innovation (in log) at different lags on the logarithm of the top 1% income share. Panel data IV (2 SLS) regressions with both instrument (appropriation and spillover) for column 1 to 6 and OLS for column 7. State fixed effects and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality Innovation	**(1)** Top 1% 3YWindow	**(2)** Top 1% 3YWindow	**(3)** Top 1% patent_pc	**(4)** Top 1 % 3YWindow	**(5)** Top 1% 3YWindow	**(6)** Top 1% patent_pc	**(7)** Top 1% 3YWindow
Innovation	0.152***	0.157***	0.180***	0.174***	0.123***	0.179***	0.150***
	(3.12)	(2.93)	(3.27)	(2.76)	(3.02)	(3.28)	(3.21)
Gdppc	-0.186*	-0.168	-0.139*	-0.159*	-0.124	-0.125	-0.171*
	(-1.83)	(-1.60)	(-1.75)	(-1.73)	(-1.57)	(-1.62)	(-1.80)
Popgrowth	0.926	1.281	0.774	0.929	1.031	0.796	1.070
	(1.27)	(1.62)	(1.13)	(1.29)	(1.48)	(1.16)	(1.47)
Sharefinance	0.034**	0.024	0.024*	0.040**	0.031**	0.021	0.032**
	(2.15)	(1.39)	(1.70)	(2.23)	(2.04)	(1.57)	(1.97)
Outputgap	-3.743**	-3.987**	-2.498*	-3.587**	-4.110**	-2.615*	-3.890**
	(-2.28)	(-2.33)	(-1.74)	(-2.21)	(-2.53)	(-1.78)	(-2.39)
Gvtsize	-0.044	-0.065	-0.096**	-0.068	-0.037	-0.107**	-0.063
	(-0.73)	(-1.08)	(-2.06)	(-1.20)	(-0.66)	(-2.17)	(-1.11)
Highways	0.024***	0.019**	0.029***	0.023***	0.018**	0.029***	0.022***
	(2.78)	(2.22)	(3.31)	(2.62)	(2.30)	(3.32)	(2.69)
Military	0.012**	0.010**	0.009**	0.014**	0.011**	0.009**	0.012**
	(2.40)	(1.97)	(2.07)	(2.45)	(2.34)	(2.12)	(2.43)
Spill_Gdppc	0.524	0.398	0.211	0.712	0.480	0.273	0.898
	(1.04)	(0.67)	(0.46)	(1.25)	(0.95)	(0.58)	(1.52)
RemunFinance	0.044						
	(1.01)						
EFD				-0.598			
				(-1.58)			
Oil					-0.027***		
					(-3.47)		
					1.680***	-0.108	
					(3.31)	(-0.39)	
							0.010**
							(2.46)
R^2	0.906	0.907	0.911	0.901	0.915	0.911	0.907
1^{st} stage F-stat	19.10	15.97	25.02	13.99	20.43	26.33	19.84
N	1598	1470	1748	1598	1598	1748	1548

Table 8: Effect of various measures of innovation (in log and lagged) on the logarithm of the top 1% income share. In column (2), NY, CT, DE and SD are dropped from the dataset, in column (3), finance-related patents have been removed and in column (6), oil-related patent have been removed. Time Span: 1975-2010 for columns (3) and (6), 1975-2007 for others. Panel data IV (2 SLS) regressions with both instrument (appropriation and spillover). State-fixed effect and time dummies are added but not reported. Variable *Oil* and *NaturalRessource* measures the share of oil related and natural ressource extractions activities in GDP, variable *RemunFinance* measures the average compensation per employee in the financial sector, variable *EFD* measures the financial dependence of innovation and variable *MarginalTax* measures the highest marginal tax rate of labor. Other variables are described in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality	(1) Top 1%	(2) Top 1%	(3) Top 1%	(4) Top 1%	(5) Top 1%	(6) Top 1%
Number of star inventors	0.101**	0.129**	0.129***	0.132**	0.188**	0.174***
	(2.04)	(2.18)	(3.22)	(2.06)	(2.14)	(3.17)
Gdppc	-0.093	-0.187*	-0.137	-0.091	-0.215*	-0.145
	(-1.14)	(-1.67)	(-1.53)	(-1.11)	(-1.71)	(-1.54)
Popgrowth	-0.111	-0.026	-0.141	-0.203	-0.057	-0.254
	(-0.16)	(-0.04)	(-0.20)	(-0.28)	(-0.08)	(-0.35)
Sharefinance	0.037**	0.052**	0.045***	0.047**	0.070**	0.059***
	(2.03)	(2.48)	(2.67)	(2.12)	(2.44)	(2.88)
Outputgap	-2.103	-2.245	-2.197	-2.237	-2.554*	-2.430
	(-1.49)	(-1.55)	(-1.51)	(-1.58)	(-1.68)	(-1.64)
Gvtsize	-0.127**	-0.035	-0.107*	-0.123**	-0.003	-0.097*
	(-2.46)	(-0.53)	(-1.95)	(-2.27)	(-0.03)	(-1.65)
Highways	0.030***		0.033***	0.031***		0.034***
	(3.15)		(3.40)	(3.08)		(3.31)
Military	0.008**		0.009**	0.009**		0.011**
	(2.08)		(2.19)	(2.12)		(2.28)
Spill_Gdppc		0.218	0.314		0.404	0.487
		(0.44)	(0.65)		(0.71)	(0.93)
R^2	0.917	0.905	0.909	0.914	0.893	0.902
1st stage F-stat	24.39	17.22	19.96	18.79	13.76	15.69
N	1648	1683	1648	1648	1683	1648

Table 9: Effect of the number of top inventors per capita (in log and lagged) on the logarithm of the top 1% income shares. Time span: 1975-2007. Panel data IV (2 SLS) regressions with the number of senators on the Appropriation Committee used as an instrument in columns (1) and (4), the spillover on the number of patent per capita in columns (2) and (5) and the two instruments jointly in columns (3) and (6). States-fixed effect and time dummies are added but not reported. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of	(1)	(2)	(3)	(4)	(5)	(6)
Inequality	Top 1%	Top 1%	Gini	Gini	G99	G99
Innovation	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc
Innovation	0.047**	0.053**	-0.002	0.022*	-0.018	0.009
	(2.13)	(2.46)	(-0.17)	(1.69)	(-1.22)	(0.68)
Gdppc	0.475**	0.716***	-0.041	0.280***	-0.279**	0.115
	(2.68)	(4.11)	(-0.35)	(3.16)	(-2.25)	(1.40)
Popgrowth	-1.139*	-0.490	-0.648**	-0.221	0.107	-0.096
	(-1.99)	(-1.22)	(-2.01)	(-0.60)	(0.21)	(-0.25)
Gvtsize	-0.002**	-0.001	-0.001*	-0.000	-0.001	0.000
	(-2.13)	(-0.63)	(-1.87)	(-0.11)	(-1.44)	(0.09)
Participation Rate		-0.912***		-1.508***		-1.735***
		(-2.79)		(-6.82)		(-7.16)
School Expenditure		-0.239*		-0.232**		-0.247***
		(-1.92)		(-2.57)		(-2.77)
College per capita		-0.187*		-0.108*		-0.055
		(-1.69)		(-1.82)		(-1.05)
Employment Manuf		-0.262		-0.350**		-0.365**
		(-1.07)		(-2.03)		(-2.10)
R^2	0.173	0.189	0.034	0.228	0.101	0.335
N	660	560	670	560	660	560

Table 10: Effect of innovativeness on various measures of inequality at the commuting zone level. The measure of innovation is the log of the average number of granted patents per capita whose filed between 1992 and 1996. Columns (1) and (2) use the size of the top 1% income share group as a measure of inequality, columns (3) and (4) use the Gini index and columns (5) and (6) use the Gini index for the bottom 99%. Columns (2), (4) and (6) add additional controls. All inequalities measure are computed over the period 1996-2000. Cross sectional OLS regressions. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Mobility Innovation	(1) AM25 patent_pc	(2) P1-5 patent_pc	(3) P2-5 patent_pc	(4) AM25 patent_pc	(5) P1-5 patent_pc	(6) P2-5 patent_pc	(7) P5 patent_pc
Innovation	0.024***	0.108***	0.063***	0.019**	0.073**	0.046*	0.022
	(3.07)	(3.13)	(2.70)	(2.40)	(2.10)	(1.76)	(1.17)
Gdppc	-0.094*	-0.225	-0.204	-0.139***	-0.384*	-0.356**	-0.271**
	(-1.81)	(-1.09)	(-1.48)	(-3.33)	(-1.84)	(-2.39)	(-2.31)
Popgrowth	0.177	0.603	0.711	0.236	0.588	0.731	0.611
	(0.61)	(0.55)	(0.87)	(0.76)	(0.48)	(0.84)	(0.89)
Gvtsize	0.000	0.002	0.001	0.000	-0.000	-0.001	-0.000
	(1.43)	(1.30)	(0.84)	(0.06)	(-0.19)	(-0.77)	(-0.37)
Participation Rate	0.600***	1.356**	1.274**	0.726***	2.067***	1.692***	1.087**
	(3.76)	(2.19)	(2.45)	(4.50)	(3.22)	(3.14)	(2.55)
School Expenditure	0.116**	0.550**	0.349**	0.096*	0.417**	0.298*	0.153
	(2.07)	(2.65)	(2.20)	(1.81)	(2.05)	(1.91)	(1.36)
College per capita				0.081	0.075	0.081	0.119
				(1.52)	(0.35)	(0.49)	(0.98)
Employment Manuf				-0.333***	-1.566***	-1.273***	-0.677***
				(-3.43)	(-4.27)	(-4.18)	(-2.86)
R^2	0.201	0.182	0.163	0.243	0.215	0.211	0.160
N	637	645	645	546	546	546	546

Table 11: Effect of innovativeness on social mobility at the commuting zone level. Columns (1) and (4) test the effect of the number of patents per capita on absolute upward mobility when the parent percentile is set to 25. Columns (2), (3), (5) and (6) test the effect of the number of patents per capita on the probability for a child at 30 to reach the 5^{th} quintile in global income distribution if parents belonged to quintile 1 for columns (2) and (5) and 2 for columns (4) and (6), 3 for column (5) and 4 for column (6). Column (7) tests the effect of the log number of patents per capita on the overall probability to reach the 5^{th} quintile in global income distribution if parents belonged to any lower quintile. Cross-Section OLS regressions. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Mobility Innovation	(1) AM25 patent_pc	(2) P1-5 patent_pc	(3) P2-5 patent_pc	(4) AM25 patent_pc	(5) P1-5 patent_pc	(6) P2-5 patent_pc	(7) AM25 patent_pc
Innovation from Entrants	0.016** (2.61)	0.058** (2.39)	0.038** (2.11)				0.018** (2.61)
Innovation from Incumbent				0.007 (0.87)	0.032 (0.97)	0.020 (0.75)	-0.006 (-0.64)
Gdppc	-0.136*** (-3.08)	-0.381* (-1.78)	-0.330** (-2.11)	-0.136*** (-2.96)	-0.405* (-1.87)	-0.340** (-2.14)	-0.128*** (-2.83)
Popgrowth	0.287 (1.00)	0.757 (0.66)	0.827 (0.98)	0.272 (0.92)	0.708 (0.61)	0.792 (0.93)	0.290 (1.02)
Gvtsize	0.000 (0.04)	-0.000 (-0.22)	-0.001 (-0.80)	0.000 (0.08)	-0.000 (-0.21)	-0.001 (-0.76)	0.000 (0.07)
Participation Rate	0.785*** (4.61)	2.291*** (3.44)	1.815*** (3.25)	0.758*** (4.48)	2.180*** (3.30)	1.743*** (3.14)	0.799*** (4.71)
School Expenditure	0.109** (2.09)	0.467** (2.38)	0.322** (2.04)	0.102* (1.95)	0.442** (2.24)	0.306* (1.95)	0.111** (2.10)
College per capita	0.081* (1.70)	0.068 (0.36)	0.090 (0.57)	0.075 (1.57)	0.036 (0.19)	0.071 (0.44)	0.084* (1.81)
Employment Manuf	-0.312*** (-3.16)	-1.508*** (-4.12)	-1.212*** (-3.95)	-0.366*** (-3.70)	-1.705*** (-4.54)	-1.341*** (-4.34)	-0.307*** (-3.04)
R^2	0.260	0.233	0.221	0.243	0.217	0.209	0.261
N	541	541	541	541	541	541	541

Table 12: Effect of innovativeness on social mobility at the commuting zone level. Columns (1) and (4) test the effect of the number of patents per capita on absolute upward mobility when the parent percentile is set to 25. Columns (2) and (5) (resp (4) and (6)) test the effect of the number of patents per capita on the probability for a child at 30 to reach the 5^{th} quintile in global income distribution if parents belonged to quintile 1 (resp 2). Columns (1) to (3) focus on "entrant patents" while columns (4) to (6) focus on "incumbent patents" and column (7) add the two kinds of innovation in a horse race regression. Cross-Section OLS regressions. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of Inequality Innovation	(1) top 1% patent_pc	(2) top 1% patent_pc	(3) top 1% patent_pc	(4) top 1% Citations	(5) top 1% Citations	(6) top 1% Citations
Innovation from Entrants	0.032*** (2.97)		0.030*** (2.69)	0.018*** (2.74)		0.017** (2.44)
Innovation from Incumbents		0.017** (2.32)	0.014* (1.83)		0.014** (2.33)	0.012* (1.94)
Gdppc	-0.140** (-2.35)	-0.134** (-2.32)	-0.158** (-2.57)	-0.115* (-1.85)	-0.119** (-1.97)	-0.128** (-2.03)
Popgrowth	0.797 (1.18)	0.817 (1.21)	0.945 (1.41)	0.394 (0.54)	0.437 (0.59)	0.386 (0.53)
Sharefinance	0.006 (0.49)	0.015 (1.14)	0.007 (0.53)	0.017 (1.25)	0.017 (1.24)	0.018 (1.34)
Outputgap	-3.732** (-2.36)	-3.802** (-2.49)	-3.863** (-2.46)	-3.829** (-2.45)	-3.827** (-2.40)	-3.772** (-2.38)
Gvtsize	-0.012 (-0.26)	-0.013 (-0.29)	0.008 (0.18)	-0.059 (-1.20)	-0.071 (-1.49)	-0.062 (-1.32)
R^2	0.907	0.907	0.908	0.903	0.903	0.904
N	1581	1581	1581	1377	1377	1377

Table 13: Effect of innovativeness (in log and lagged) on inequality measured by the logarithm of the share of income held by the richest 1%. Columns (1) and (4) restrict the sample on entrant patents, columns (2) and (5) focus on incumbent patents and columns (3) and (6) use both innovation in a horse race. Time Span: 1979-2009 for columns (1), (2) and (3), 1981-2006 for others. Panel data OLS regressions. States fixed effect and time dummmies are added but not reported. Variable descriptions are given in table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

Measure of	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inequality	top 1%	top1%	top 1%	-	-	-	-
Mobility	-	-	-	AM25	AM25	AM25	AM25
Innovation	3YWindow	3YWindow	3YWindow	patent_pc	patent_pc	patent_pc	patent_pc
Innovation	0.059***		0.153***				
	(6.06)		(3.81)				
from Entrants		0.020***		0.012	0.028***		
		(3.71)		(1.28)	(2.72)		
from Incumbents		0.012*				0.005	0.014
		(1.87)				(0.73)	(1.46)
*Lobbying*Innovation*	-0.060***		-0.074***				
	(-9.48)		(-10.01)				
from Entrants		-0.034***					
		(-6.79)					
from Incumbents		-0.004					
		(-0.65)					
Gdppc	-0.093*	-0.071	-0.200**	0.044	0.030	0.046	0.028
	(-1.65)	(-1.33)	(-2.20)	(1.66)	(0.94)	(1.68)	(0.81)
Popgrowth	0.445	0.097	1.229*	0.002	0.000	0.003	0.000
	(0.71)	(0.15)	(1.72)	(1.47)	(0.16)	(1.64)	(0.16)
Sharefinance	0.016	0.009	0.024	0.000	-0.003***	0.000	-0.003**
	(1.21)	(0.64)	(1.58)	(0.15)	(-2.82)	(0.40)	(-2.19)
Outputgap	-1.930	-2.201	-2.550				
	(-1.36)	(-1.61)	(-1.57)				
Gvtsize	0.008	-0.044	0.064	-0.001	0.001	-0.001	0.001
	(0.19)	(-1.04)	(1.12)	(-0.41)	(0.78)	(-0.47)	(0.86)
Highways			0.032***				
			(3.80)				
Military			0.005				
			(0.99)				
Spill_Gdppc			0.983**				
			(2.01)				
R^2	0.925	0.925	0.922	0.107	0.079	0.100	0.049
1st stage F-stat	-	-	11.79	-	-	-	-
N	1632	1632	1598	176	176	176	176

Table 14: Effect of innovativeness (in log and lagged) on inequality and social mobility, breakdown using lobbying intensity and origin of innovation. Column (1) presents results from an OLS regression at the cross state level for every patent citations while Column (2) uses entrant patents and incumbent separately (in a OLS horse-race regression). Column (3) uses the measure of spillover as an instrument variable. Panel regressions with a time span of 1975-2006, 1979-2006 and 1979-2006. Time dummies and states fixed effect are added but not reported. Columns (4) to (7) present results from an OLS regression at the cross-MSA level with robust standard errors clustered at the state level. Columns (4) and (6) restrict the sample to MSA that are above median in terms of lobbying activity, columns (5) and (7) focus on MSA below this median. Lobbying*Innovation stands for the interacting terms between innovativeness and a dummy for being above median in terms of lobbying activities, other Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

8 Appendix

8.1 Proofs for Section 2.2.3

From (11), we have:

$$\frac{\partial \tilde{x}^*}{\partial \eta_L} = -\frac{1}{\eta_L^2}\frac{1}{\theta_I} < 0,$$

whereas:

$$\frac{\partial x^*}{\partial \eta_L} = (1-z)\,\frac{\begin{array}{c}[(1-2\tilde{x}^*)\left(\theta_E - (1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)\\ -\left(\pi_H - \frac{1}{\eta_L}(1-\tilde{x}^*) - \frac{1}{\eta_H}\tilde{x}^*\right)(1-z)^2]\end{array}}{\eta_L^2\left(\theta_E - (1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)^2},$$

the sign of which is ambiguous—intuitively a higher η_L decreases incumbent's rate which increases wages but also has a direct negative impact on wages and higher wages in turn lower entrant innovation.

However, when $\theta_E = \theta_I$, the overall effect of a higher η_L on the aggregate innovation rate is negative; more formally:

$$\begin{aligned}
& \frac{\partial \tilde{x}^*}{\partial \eta_L} + \frac{\partial x^*}{\partial \eta_L} \\
= \; & -\frac{1}{\eta_L^2}\frac{1}{\theta} + \frac{(1-z)(1-\tilde{x}^*)}{\eta_L^2\left(\theta - (1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)} \\
& -(1-z)\,\frac{\tilde{x}^*\left(\theta - (1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right) + \left(\pi_H - \frac{1}{\eta_L}(1-\tilde{x}^*) - \frac{1}{\eta_H}\tilde{x}^*\right)(1-z)^2}{\eta_L^2\left(\theta - (1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)^2} \\
= \; & -\frac{1}{\eta_L^2\left(\theta - (1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)} \\
& \left(\begin{array}{c} \frac{z}{\theta}\left(\theta + (1-z)\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right) \\ +(1-z)\,\frac{\tilde{x}^*\left(\theta-(1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)+\left(\pi_H-\frac{1}{\eta_L}(1-\tilde{x}^*)-\frac{1}{\eta_H}\tilde{x}^*\right)(1-z)^2}{\left(\theta-(1-z)^2\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\right)} \end{array}\right) \\
< \; & 0.
\end{aligned}$$

Overall, we therefore have:

$$\frac{\partial entrepreneur\_share_t}{\partial \eta_L} = \frac{1}{\eta_L^2}\left(1-(1-z)x^* - \tilde{x}^*\right) + \left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)\frac{\partial}{\partial \eta_L}\left((1-z)x^* + \tilde{x}^*\right),$$

where the second term is dominated by the first term for θ large enough.

8.2 First stage and reduced form from the IV regressions

In Table 15, we present outputs from the reduced form (when direclty regressing our instruments on the logarithm of the top 1% income share) and the first stage regressions. Columns 1 and 2 use our two instruments jointly, columns 3 and 4 use only the spillover instrument and columns 5 and 6 use the senate appropriation committee based instrument.

Measure of	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Inequality	top 1%	-	top 1%	-	top 1%	-
Innovation		patent_pc		patent_pc		patent_pc
Appropriation Committee	0.012**	0.077***			0.011**	0.076***
	(2.17)	(5.33)			(2.13)	(5.27)
Spillover	0.209***	1.089***	0.174**	1.098***		
	(2.84)	(4.77)	(2.44)	(4.63)		
Gdppc	-0.016	0.653***	-0.050	0.647***	0.021	0.789***
	(-0.27)	(4.97)	(-0.86)	(5.35)	(0.41)	(6.33)
Popgrowth	0.495	-1.978	0.400	-2.759**	0.281	-2.952**
	(0.75)	(-1.41)	(0.67)	(-2.11)	(0.43)	(-2.09)
Sharefinance	0.013	-0.071**	0.019	-0.048	0.003	-0.124***
	(0.99)	(-1.97)	(1.55)	(-1.36)	(0.22)	(-3.24)
Outputgap	-2.136	2.182	-2.007	2.845	-1.952	2.691
	(-1.56)	(0.96)	(-1.49)	(1.29)	(-1.45)	(1.18)
Gvtsize	-0.094**	0.082	-0.060	-0.028	-0.137***	-0.116
	(-2.01)	(0.58)	(-1.37)	(-0.20)	(-3.18)	(-0.87)
Highways	0.022***	-0.039**			0.019***	-0.059***
	(3.05)	(-2.12)			(2.70)	(-3.23)
Military	0.005	-0.018***			0.005	-0.013**
	(1.35)	(-3.02)			(1.48)	(-2.22)
Spill_Gdppc	0.129	-0.785	0.029	-0.303		
	(0.31)	(-0.73)	(0.07)	(-0.29)		
N	1798	1748	1836	1785	1798	1748

Table 15: Results from the reduced form equation (columns 1, 3 and 5) and the first stage regressions (columns 2, 4 and 6) when the number of patent per capita (in log and lagged) is used as a Measure of innovation. Panel OLS regressions. Variable description is given in table 1.$***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

8.3 Looking at industry composition

Measure of Inequality Innovation	**(1)** Top 1% patent_pc	**(2)** Top 1% patent_pc	**(3)** Top 1% patent_pc	**(4)** Top 1 % patent_pc	**(5)** Top 1% patent_pc	**(6)** Top 1% patent_pc
Innovation	0.298*** (2.96)	0.177*** (3.28)	0.181*** (3.28)	0.192*** (3.17)	0.239*** (3.00)	0.165*** (3.27)
Gdppc	-0.090 (-1.24)	-0.135* (-1.72)	-0.141* (-1.77)	-0.164** (-2.02)	-0.045 (-0.69)	-0.154* (-1.83)
Popgrowth	0.402 (0.62)	0.766 (1.12)	0.783 (1.14)	0.645 (0.92)	-0.021 (-0.03)	0.860 (1.23)
Sharefinance	-0.003 (-0.19)	0.024* (1.71)	0.024* (1.69)	0.011 (0.83)	0.020 (1.33)	0.024* (1.72)
Outputgap	-2.238 (-1.58)	-2.486* (-1.73)	-2.453* (-1.71)	-2.200 (-1.52)	-1.707 (-1.26)	-2.702* (-1.82)
Gvtsize	-0.083 (-1.61)	-0.096** (-2.07)	-0.098** (-2.10)	-0.092* (-1.96)	-0.161*** (-3.05)	-0.083* (-1.74)
Highways	0.026*** (2.81)	0.029*** (3.34)	0.029*** (3.33)	0.029*** (3.35)	0.026*** (2.84)	0.029*** (3.34)
Military	0.015*** (2.63)	0.009** (2.04)	0.009** (2.09)	0.010** (2.32)	0.012** (2.51)	0.008** (1.96)
Spill_Gdppc	0.570 (1.01)	0.203 (0.44)	0.169 (0.37)	-0.372 (-0.78)	0.105 (0.22)	0.372 (0.76)
Size of sector						
Computer and Electronic Products				0.016 (0.87)		
Chemistry				0.052*** (2.61)		
Electrical equipment				-0.020 (-1.63)		
R^2	0.898	0.911	0.911	0.910	0.900	0.909
1st stage F-stat	14.55	25.84	24.88	21.47	15.30	24.25
N	1748	1748	1748	1748	1748	1748

Table 16: Effect of the number of patents per capita in some specific sectors (in log and lagged) on the logarithm of the top 1% income share. Column (1) excludes patents from the computer sectors (NAICS: 334), column (2) excludes patents from the pharmacetical sectors (NAICS: 3254) and column (3) excludes patents from the electrical equipment sectors (NAICS: 335). Columns (5) focus on patents from three highly exporting sectors: Transportation, Machinery and Electrical Machinery while column (6) excludes these sectors. The size of a sector (see column (4)) is defined as the gdp per capita from the corresponding sector. Panel data IV (2 SLS) regressions with both instrument (appropriation and spillover). Time span: 1975-2010. Variable description is given in Table 1. $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.

8.4 Regressions with control for agglomeration effects

In Table 17, we include different proxies to control for agglomeration effects (see text). These proxies have all been constructed using patent data to look at the most innovative classes in each state and each year and to count the number of different assignees that patent in these classes. Columns 1 does not include this proxy and is here as a benchmark. Columns 2 to 5 include different varieties of the same proxy and column 6 is an OLS regression. In all cases, our results remain significant and positive and the effect of innovation on the top 1% income share is only slightly affected. Note that in order to address the truncation bias issue, we had to stop the regression in 2005, this explains why column 1 shows a different coefficient for innovation than previous regressions.

Measure of Inequality Innovation	(1) top 1% Y3Windows	(2) top 1% Y3Windows	(3) top 1% Y3Windows	(4) top 1% Y3Windows	(5) top 1% Y3Windows	(6) top 1% Y3Windows
Innovation	0.200***	0.200***	0.199***	0.198***	0.199***	0.023**
	(3.25)	(3.30)	(3.33)	(3.34)	(3.32)	(2.22)
Gdppc	-0.138	-0.141	-0.134	-0.128	-0.121	-0.070
	(-1.55)	(-1.63)	(-1.59)	(-1.54)	(-1.49)	(-1.17)
Popgrowth	0.201	0.203	0.178	0.155	0.167	-0.060
	(0.28)	(0.28)	(0.25)	(0.22)	(0.23)	(-0.09)
Sharefinance	0.039**	0.039**	0.038**	0.038**	0.038**	0.020
	(2.27)	(2.28)	(2.27)	(2.25)	(2.27)	(1.40)
Outputgap	-2.478*	-2.495*	-2.441*	-2.421	-2.400	-2.337*
	(-1.67)	(-1.69)	(-1.66)	(-1.64)	(-1.64)	(-1.66)
Gvtsize	-0.157***	-0.154***	-0.160***	-0.164***	-0.169***	-0.112**
	(-2.85)	(-2.78)	(-2.92)	(-3.00)	(-3.09)	(-2.45)
Highways	0.029***	0.029***	0.029***	0.028***	0.028***	
	(3.08)	(3.19)	(3.18)	(3.14)	(3.12)	
Military	0.012***	0.012***	0.011**	0.011**	0.012***	
	(2.59)	(2.58)	(2.54)	(2.52)	(2.58)	
Spill_Gdppc	0.365	0.358	0.376	0.373	0.390	
	(0.78)	(0.76)	(0.79)	(0.79)	(0.82)	
Agglo1		0.002	0.003	0.003		
		(0.42)	(0.55)	(0.64)		
Agglo2			-0.006	-0.005		
			(-1.23)	(-1.18)		
Agglo3				-0.005		
				(-1.00)		
Agglo123					-0.010	0.013*
					(-0.96)	(1.92)
R^2	0.904	0.904	0.904	0.904	0.904	0.915
N	1598	1548	1548	1548	1548	1581

Table 17: Effect of innovativeness measured by the number of citations within a 3 year citation window on the top 1% income share. Robustness including additional controls to proxy for agglomeration effects: Agglo1, Agglo2, Agglo3 and Agglo123 are the log of the number of firms in the first, second, third and three most innvoative sector(s) for each state and year (all lagged). Panel data IV (2 SLS) regressions with both instrument (appropriation and spillover) except for column 6 in which it is OLS. Time span:1975-2005. Other variables are described in table 1.$***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$; t/z statistics in brackets, computed with robust standard errors.