Innovation and Top Income Inequality

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Abstract

In this paper we use cross-state panel data to show a positive and significant correlation between innovativeness and top income inequality in the United States over the past decades. Our instrumentation at cross-state level suggests that this correlation (partly) reflects a causality from innovativeness to top income inequality. Next, using cross commuting zones (CZ) data, we show that innovativeness is positively and significantly correlated with social mobility, and that this correlation is driven mainly by entrant innovators and less so by incumbent innovators. In addition, the positive effects of innovation on the top 1% income share and on social mobility are both dampened in states with higher lobbying intensity. Overall, our findings are in line with the Schumpeterian view whereby the rise in top income shares in developed countries and particularly in the US over the past decades, is at least partly related to innovation-led growth, where innovation itself fosters social mobility at the top through the process of creative destruction.

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1 Introduction

Do high incomes result primarily from the accumulation of capital revenues by inheritors, or do they also reflect successful entrepreneurial innovations? The answer to this question has important implications. In particular, if we believe that income inequality at the top of the income distribution results primarily from capital accumulation by already wealthy individuals (notably inheritors), then taxing capital income and wealth at higher rates is a natural way to counter the polarization of wealth and income while fostering social mobility. If instead it appears that increases in top incomes result at least partly from entrepreneurial innovations, then overtaxing capital income could discourage innovation; and to the extent that innovation involves *creative destruction,* i.e. the replacement of existing producers by new producers, this in turn may even end up reducing social mobility. In this case tax policy and entry policy could be used in tandem to provide a balance between innovation and inequality. In this paper we use cross-state panel data over the period 1995-2010 to look at the effect of innovativeness on top income inequality. Then we use cross Commuting-zone data from Chetty et al (2015) to look at the effect of innovativeness on social mobility.[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 both: (i) fosters innovation and thus increase the rate of (frontier) growth; (ii) increase the top income share since top incomes are earned by innovators; and (iii) spurs social mobility as employees' children more easily become business owners and vice versa. In particular, this Schumpeterian model predicts a positive correlation between innovation-led growth on the one hand, and top income shares and social mobility on the other hand.

These predictions are not unreasonable at first sight: for example California is the most technologically advanced and the most innovative state in the US; but it is also the state where the richest 1% receives more than 20% of total income[2] and it lies among the US states with the highest levels of social mobility (see Chetty et al, 2013)); similarly, in Scandinavian countries, innovation-led growth has accelerated and top income shares have increased in the decade after the mid 1990s relative to the previous decade, while in the meantime, social mobility has not decreased. In this paper we go one step further and confront the above predictions to more systematic cross state (and then cross-commuting zones and cross MSA) panel evidence.

Our main findings can be summarized as follows. First, the top 1% income share in the US is positively and significantly correlated with frontier growth (i.e. productivity growth by states close the technological frontier), but not with non-frontier growth.[3] Next, the top 1% income share is positively and

[1] Where social mobility is measured by the probability of raising from bottom to top of the income ladder (see Chetty et al, 2015).

[2] Data for 2010, see below for details.

[3] Parallel work by Acemoglu and Robinson (2015) also reports a positive correlation between

significantly correlated with the state's degree of innovativeness, i.e. with the quality-adjusted amount of innovation in this country or state, which we measure by: (i) citation count; (ii) a dummy variable equal to one if the patent applied for in a given year belong to the 5% most cited patents; (iii) a dummy equal to one if the patent has been renewed (at least once) before 2014. 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 and the House of Representatives,[4] and second by relying on knowledge spillovers from the other states. 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.

Next, from cross-section regressions performed at the CZ level,[5] we find that innovativeness is positively correlated with upward social mobility as measured by the probability that a child makes it to a top income bracket if her parents belonged to a lower income bracket.

Finally, we show that the positive effects of innovativeness on social mobility, is driven mainly by entrant innovators and less so by incumbent innovators. In addition, the positive effects of innovation on the top 1% income share and on social mobility are both dampened in states with higher lobbying intensity; to the extent that lobbying is likely to reduce entry, these results emphasize the role played by entrant innovators in the relationship between innovativeness, top income inequality and social mobility.

Our results pass a number of robustness tests: in particular the positive and significant correlations between innovativeness and top income shares in cross state panel regressions, is robust to controlling for infrastructure investment; to controlling for the share of the financial sector in state GDP and for dependence on external finance; to controlling for the share of oil extraction related activities in state GDP or to removing energy-related patents from our patenting sample. It is also robust to including top marginal tax rates as control variables (whether on capital, labor or interest income).

Overall, our findings are in line with the Schumpeterian view whereby more innovation-led growth should both, increase top income shares (which reflect innovation rents) and social mobility (which results from creative destruction and associated firm and job turnover).

The analysis in this paper relates to several strands of literature on income inequality and growth. First, to endogenous growth models: thus Rebelo

top income inequality and growth in panel data at the country level (or at least no evidence of negative correlation). However, the main focus of their paper is on the role played by institutions in determining inequality, whereas our own focus is on the (causal) relationship between innovation-led growth and both, top income shares and social mobility. Moreover, we use US cross-state and cross-commuting zones panel data which allows us both, to get more significant regression coefficients and also to instrument for innovation-led growth.

[4]Following Aghion et al. (2004).

[5]Here, we build on Chetty et al. (2013).

(1991) developed an AK model to argue that (over)taxing capital can be detrimental to growth as capital accumulation amount to knowledge accumulation in AK models, thus taxing capital slows down the accumulation of knowledge and thereby productivity growth; similarly, a straightforward implication of the 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. On the other hand, Banerjee and Newman (1993), Galor and Zeira (1993), Benabou (1996) and Aghion and Bolton (1997) argue that once credit constraints are present then reducing wealth inequality can actually have a stimulating effect on growth, as it allows credit-constrained individuals otherwise subject to credit-rationing to finance innovative projects. 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. More recently, Jones and Kim (2014) model an economy where incumbents exert efforts to increase their market share while entrants can innovate to replace the incumbents. The interplay between these two forces ensure a Pareto distribution of income, where top income inequality is negatively correlated with innovation[6] and with social mobility, a prediction at odds with our empirical results.

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.

Third, a large literature on skill-biased technical change aims at explaining the increase in labor income inequality since the 1970's. 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 which adapt faster to the detriment of the rest of the population. Krusell, Ohanian, Ríos-Rull and Violante (2000) show how with capital-skill

[6] To be more specific, the negative correlation between top income inequality and innovation depends on the fact that Jones and Kim define "innovation" as the results of the innovative efforts by the entrants, but one could think that some of the incumbents' efforts to increase their market share in fact take the form of innovations, in which case the negative correlation is not as clear.

complementarity, the increase in the equipment stock can account for the increase in the skill premium. 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 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).

Finally, 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). Several explanations have been put forward to account for this phenomenon. One explanation is based on "superstars" considerations (Rosen, 1981) and 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. Thus 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. What we add is an explicit analysis of how innovativeness affects top income shares and social mobility.

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 discussed three extensions of our analysis: first, it looks at the relationship between innovativeness and social mobility; second, it distinguishes between entrant and incumbent innovation when looking at the effects on top incomes and on social mobility; third, it looks at how local lobbying impacts on the effects of innovativeness on top income and on social mobility. 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.[7] Each individual

[7] One can extend the analysis to the more general case where workers' population differs from business owners' population. All our results would go through but the mathematical

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.

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.

2.1.2 Innovation

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

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

Therefore upon a new innovation in period t, the technological leader (who has the highest labor productivity) has a technological lead of η_H against its potential competitors in the sector.

At the end of period t, other firms copy part of the technology of the leader and therefore if there is no new innovation in period $t+1$, the incumbent's technological lead shrinks to η_L where $\eta_L < \eta_H$. When there is a new innovation in a given sector i, the previous technology becomes fully available to every firm in the economy, therefore the maximum amount of technological lead is η_H. However, an incumbent can use lobbying to prevent entry by an innovator. Lobbying is successful with probability z, in which case, the innovation is not implemented.

Both potential new entrants and incumbents have access to the following innovation technology. By spending

$$C_t(x) = \left[\beta x + \theta \frac{x^2}{2}\right] Y_t$$

an incumbent or entrant can innovate with probability x. The parameters β and θ inversely measure R&D productivity.

expressions would be a bit more complicated as we then have to carry around the mass of workers through all the equilibrium equations of the model.

2.1.3 Timing of Events

Each period unfolds as follows:

1. In each line i, a potential entrant spends $C_t(x_i)$ and the offspring of the incumbent in sector i spends $C_t(\tilde{x}_i)$.
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.[8]
3. Production and consumption takes place and the period ends.

2.2 Solving the model

2.2.1 Equilibrium profits and wages

Note that the marginal cost of production of intermediate producer i at time t in (2) is

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

Hence the price charged at time t by intermediate producer i is simply

$$p_{i,t} = \frac{w\eta_{it},}{q_{i,t}}$$

where $\eta_{i,t} \in \{\eta_H, \eta_L\}$ depending on when the last innovation occurred (recall that recent technologies have higher markups). The quantity produced is:

$$y_{it} = \frac{Y_t q_{i,t}}{w\eta_{it}}. \tag{3}$$

The producer's labor demand is:

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

Equilibrium profits in sector i at time t are given by:

$$\pi_{it} = \frac{\eta_{it}-1}{\eta_{it}} Y_t,$$

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

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

[8] For simplicity, we rule out the possibility that both innovate, so that innovations by the incumbent and the entrants are not independent events.

Finally, labor market clearing implies that:

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

where 1 is total labor supply, the right-hand side is total labor demand, and μ_t is the fraction of sectors with high markups at time t. This yields the following expression for equilibrium wages:

$$w_t = Y_t \left[\frac{\mu_t}{\eta_H} + \frac{1-\mu_t}{\eta_L} \right] \tag{4}$$

Since mark-ups are larger in sectors with new technologies, when the fraction of product lines with new technologies μ_t increases, then aggregate income shifts from workers to entrepreneurs in relative terms. More formally, the share of income earned by workers (wage share) in the economy at time t is defined as:

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

whereas the entrepreneur share is:

$$entrepreneur\_share_t = \frac{Y_t - w_t}{Y_t} = 1 - \frac{\mu_t}{\eta_H} - \frac{1-\mu_t}{\eta_L}$$

In particular we immediately see that the wage share is decreasing whereas the entrepreneur share is increasing in the fraction of high-mark-up sectors μ_t.

2.2.2 Equilibrium innovation

Now we turn to the endogenous determination of the equilibrium fraction μ_t of high-markup sectors. For that purpose, we need to solve for the equilibrium innovation decision of entrants and incumbents. The offspring of the previous period's incumbent solves the following maximization problem:

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

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

$$\tilde{x} = \max \left\{ (\pi_H - \pi_L - \beta) / \theta, 0 \right\}.$$

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

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

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

$$x = \max\left\{ \frac{\left(\pi_H - \left[\frac{\mu_t}{\eta_H} + \frac{1-\mu_t}{\eta_L}\right]\right)(1-z) - \beta}{\theta}, 0 \right\} \tag{5}$$

where we substituted for the wage rate w_t using (4).[9]

To complete the model, we need to solve for the equilibrium fraction of high mark-up sectors μ_t. By definition, μ_t is the fraction of sectors that just received a new innovation, since the innovation rates depend on t only through their dependence on μ_t, we get that μ_t is constant given by:

$$\mu_t = \mu^* = (1-z)\, x^* + \tilde{x}^* \tag{6}$$

where x^* and $\tilde{x}^*$ are the equilibrium values of entrant and incumbent innovation rates. To simplify the analysis, we assume that

$$\pi_H - \pi_L < \beta,$$

which implies that the incumbent does not innovate,[10] so that

$$\tilde{x}^* = 0 \text{ and } \mu^* = (1-z)\, x^*. \tag{7}$$

Combining (5) and (7), the equilibrium of the model simply boils down to the following expression

$$x^* = \max\left\{ \frac{1}{\theta}\left[\left(\pi_H - \left[\frac{x^*(1-z)}{\eta_H} + \frac{1-x^*(1-z)}{\eta_L}\right]\right)(1-z) - \beta\right], 0\right\}.$$

Assuming there is positive entry, the equilibrium entry rate is

$$x^* = \frac{(\pi_H - 1/\eta_L)(1-z) - \beta}{\theta - (1-z)^2 (1/\eta_L - 1/\eta_H)}.$$

In particular more barriers to entry (i.e. a higher z) and more costly R&D (i.e. higher θ or β) reduce the entrants' innovation rate (as $1/\eta_L - 1/\eta_H > 0$).

Positive entry is guaranteed by the following assumption which we shall make henceforth:

$$\left(\pi_H - \frac{1}{\eta_L}\right)(1-z) > \beta \text{ and } \theta > \left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)(1-z)^2.$$

[9] Note that we also count as "innovations" the innovations that are blocked by the incumbent (that is, we refer to x as our measure of innovation instead of $(1-z)\,x$). This, however, has no bearing on our results.

[10] In the Appendix we look at the more general case where incumbents also innovate in equilibrium.

2.2.3 Equilibrium growth rate

Substituting the equilibrium level of output into the final goods production function we find

$$w_t = \frac{Q_t}{\eta_H^{\mu^*} \eta_L^{1-\mu^*}}.$$

where Q_t is the quality index defined as $Q_t = \exp \int_0^1 \ln q_{it} di$. The above expression makes it clear that the growth rate of aggregate variables such as aggregate output and the wage rate is equal to the growth rate of the quality index Q_t.

The law of motion for the quality index is computed as

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

Hence the equilibrium growth rate is a constant given by

$$g^* = \eta_H^{x^*(1-z)} - 1,$$

which is increasing in x^* (but less so as the barriers to entry z increase).

2.2.4 Income distribution

From the above analysis, and using the fact that $\mu_t = (1-z) x^*$, the wage and entrepreneur income shares in equilibrium are simply given by:

$$wage\_share_t = \frac{w_t}{Y_t} = \frac{1}{\eta_L} - \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right) (1-z) x^*$$

whereas the capital income share is:

$$entrepreneur\_share_t = \frac{Y_t - w_t}{Y_t} = \frac{\eta_L - 1}{\eta_L} + \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right) (1-z) x^*.$$

Thus anything that increases equilibrium innovation rates x^* also increases the entrepreneur share at the expense of the wage share. This effect is lower when barriers to entry (z) are larger.

Facilitating entry (lower barriers to entry z) also directly increases the entrepreneur income share (but this prediction is not robust to having z also affect the probability of successful imitation).

2.2.5 Social mobility

The probability that an offspring of a worker has the same occupation as the parent is

$$\Psi = 1 - x^* (1-z). \tag{8}$$

Likewise, the probability that an offspring of a firm owner has the same occupation as the parent is also given by Ψ. Hence we define social mobility as

$$1 - \Psi = x^* (1-z),$$

which is increasing in the innovation rate but less so for higher entry barriers. Now we can state our results.

Proposition 1 *An exogenous increase in the innovation rate x^* leads to (i) higher aggregate growth, (ii) higher entrepreneur share, and (iii) higher social mobility but less so if barriers to entry z are high. An increase in R&D productivity (that is a reduction in θ or β), leads to an increase in the (entrants') innovation rate x^* but less so the higher entry barriers are; consequently, it leads to higher growth, entrepreneur share and social mobility but less so the higher entry barriers are.*

Proof. The only claim we have not already proved in the text is that $\frac{\partial^2}{\partial\theta\partial z}(1-z)\,x^* > 0$ and $\frac{\partial^2}{\partial\beta\partial z}(1-z)\,x^* > 0$ (which immediately implies that the positive impact of a increase in R&D productivity on growth, capital income share and social mobility is attenuated when barriers to entry are high).

Differentiating first with respect to θ, we get:

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

which is increasing in z since x^* and $(1-z)$ both decrease in z and the denominator $\theta+(1-z)^2\left[\frac{1}{\eta_H}-\frac{1}{\eta_L}\right]$ increases in z (recall that $\frac{1}{\eta_H}-\frac{1}{\eta_L}<0$).

Similarly, differentiating first with respect to β, we get:

$$\frac{\partial(1-z)\,x^*}{\partial\beta} = \frac{-(1-z)}{\theta+(1-z)^2\left[\frac{1}{\eta_H}-\frac{1}{\eta_L}\right]},$$

which is also increasing in z. This establishes the proposition. ■

Proposition 1 summarizes the predictions which we now confront with the data, taking the view that the top 1% income share and the entrepreneurs' share of income are strongly correlated.

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% and the top 10% 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 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. Graph 2 shows the evolution of the top 1% share for the state of New York and Iowa.

GRAPH 2 ABOUT HERE

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 over-represented in the top 1% income relative to wage income, suggests that our model captures an important aspect (innovation) in the evolution of top income inequality.

3.2 Innovation

When looking at cross state or more local levels, the US patent office (USPTO) provides 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 assignees, 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 assignee and since coauthors of a given patent do not necessarily live in the same state, we assume that patents are split evenly between assignees and thus we attribute only a fraction of the patent to each assignee.

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.
- Plant patents that protect some new varieties of plants.

Among those three types of patents, the first is presumably the best proxy for innovation. Moreover, it accounts for more than 90% of all patents at the USPTO and it is the only type of patents for which we have complete data. We thus focus on utility patents, in line with the patenting literature.

3.2.1 Truncation Bias

We follow the methodology developed by Jaffe, Hall and Trajtenberg (2001) (henceforth HJT) to address the issue of truncation bias in both the number of patents and the number of citations.

The bias in patent count stems from the fact that the process of granting a patent takes about two years on average. As the 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 of the sample (as many patents whose application date is close to 2010 are unlikely to be granted by 2010, and to appear in the database). Since we restrict attention to patents with application date between 1975 and 2010, the truncation bias is not an issue at the beginning of the time period (that is, correcting for patents that were granted after 1975 but whose application date was before 1975). However, we need to correct for the fact that we do not observe every patent applied for during the last years in our sample.[11] To do so, we compute the distribution of lags between the application date and the granting date and we divide the number of patents in each year by the proper share in that distribution as described in HJT. To avoid inaccuracies in this process, we had to drop the year 2010 from our sample.

Similarly, we correct for truncated citation bias using the quasi-structural approach proposed by HJT and extend the HJT corrector until 2010. The citation truncation bias is more tricky to address than the patent count truncation bias: first, a patent may be cited many year after it was granted; second, the

[11] 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."*

propensity to cite is highly heterogeneous within an industry class. The quasi-structural approach consists in inferring the distribution of the lag between a patent's application and the application of a citing patent using a non linear OLS estimation. To do so, two assumptions must be made about the distribution of lags: first, this distribution is the same over time; second, it is independent of the number of citations already received. 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 only be used before 2008.

In spite of these corrections, the number of granted patents in the US show a rapid decrease from 2001 to 2009 after showing an exponential increase from 1990 to 2000. The recent decrease in the number of granted patents cannot be fully explained by the truncation effect since the average lag in patent granting is around 2 years and therefore should only affect years 2008, 2009 and 2010. Two main factors seem to account for this inverted U-shaped curve. First, the information technology bubble has led many inventors to create a company in the high tech sector and to innovate faster than their competitors. This generated a patent race that stopped after the crisis in 2000. Second, the USPTO has faced a large surge in the number of patent applications since the past decade 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. De Rassenfosse *et al.* (2013) argue that in 2010, between 45 and 55% of patent applications filed in the early 2000s were still pending in 2010. This backlog in turn suggests that the lag in patent granting has increased since 2000 while our estimation based on the period 1975-2005, is biased downward.

To address this problem, we considered two different solutions. First, we completed the series after 2000 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[12] assuming a constant rate of acceptance. Second, we assumed 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. Each of these two methods has its shortcomings: the first one is noisy as it may involve including many insignificant patents and the second one underestimates innovativeness in the past decades. Fortunately, these two approaches yield very similar results and therefore we shall only present results using the first approach.[13]

There is a substantial amount of variation in innovativeness both across states and over time. Between 1975 and 1990, Delaware, Connecticut, New Jersey and Massachusetts were the most innovating states (with 0.55, 0.4, 0.39 and

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

[13]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.

0.29 patents per 1000 inhabitants respectively), while Arkansas, Mississippi and Hawaii were the least innovative states with less than 0.05 patents per thousands inhabitants. Between 1990 and 2009, however, the most innovative states were Idaho (0.99 patents per 1000 inhabitants), Vermont (0.86), Massachusetts (0.63), Minnesota (0.61) and California (0.61), whereas Arkansas, West Virginia and Mississippi all had less than 0.06 patents per 1000 inhabitants.

3.2.2 Quality measures

Simply counting the number of patent granted by their application date is a crude measure of innovativeness as it does not differentiate between a patent that made a significant contribution to science and a more incremental patent. 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 started to compute this measure for 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 one) 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 Frontier versus non-frontier productivity growth

To measure frontier versus non-frontier growth, we use cross state panel data on labor productivity. We define Labor Productivity (LP) as the real GDP per person employed because of data availability for GDP per hours worked. Accordingly, at the state level, labor productivity is computed from GDP and employment data taken from the Bureau of Economic Analysis (BEA). We divide our state sample into two groups according to their distance to the corresponding technological frontier. The frontier is defined as the state with the highest labor productivity. At the cross-country level, the frontier productivity is alternatively Norway or the US. However, when comparing across US states, the leading state changes over the period between 1975 and 2010. For each year, we compute the frontier level of productivity as the max of labor productivities across US states for that year. We then subdivide our samples into two groups: the first group (hereafter referred to as Group 1) is composed of countries/states above a given threshold in terms of their proximity to the corresponding frontier that year; the second group (hereafter referred to as Group 2) is composed of states that lie below this threshold in terms of their proximity to the corresponding frontier that year. The threshold is computed in different ways: for example, it can be taken to be the median of productivity during the year, or to be the cut-off point between the third and fourth quintile.

3.4 Control variables

When trying to explain top income shares by productivity growth and innovativeness, a few concerns might be raised. First, the business cycle has direct consequences on productivity growth, innovation and top income share. Second, top income share groups are likely to involve to a significant extent individuals employed by the financial sector (e.g. see Philippon and Reshef, 2012). To evidence this strong correlation, Graph 1 shows the evolution of the share of the financial sector and of the size of the top 1% income share group in the state of New York. In turn, the financial sector is sensitive to business cycles and it may also affect innovation and productivity growth directly. To address these two concerns, we first add output gap as a control variable in our regressions to control for the business cycle. In addition, we add a control variable equal to the share of (country or state) GDP accounted for by the financial sector. Similarly, we also control for the size of the government sector which may affect top income inequality but also innovation and productivity growth. Our final set of control variables are: GDP per capita, the growth of total population, the size of the government, the share of the financial sector and the estimated output gap; however we do not include GDP per capita as a control in regressions which focus on the impact of productivity growth because of colinearity concerns.

GRAPH 1 ABOUT HERE

Data on GDP per capita, total population and the share of financial sector can be found in the Bureau of Economic Analysis (BEA) regional accounts. From the same source, we use data on the share of GDP from the public sector to account for government size. Finally, we compute the output gap defined as the relative distance of real GDP per capita to its filtered value, namely:

$$X = \frac{Y - H(Y)}{H(Y)}, \tag{9}$$

where H represents the HP filter with 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 Empirical results

4.1 Top incomes and frontier versus non-frontier productivity growth

4.1.1 Empirical strategy

Our dependant variable is the top X% income share, with X being equal to 1 or 10 in the cross-state panel regressions. We add various control variables to the right-hand side of our regression equations, as specified above. Finally, the dependant variables are normalized so that the magnitudes of the effects implied by the regression coefficients on top 1% and top 10% incomes can be directly compared with one another, and this also applies to the other indexes of inequality we consider in this section.

As we look for evidence to the effect that growth shows a stronger correlation with top income shares for states that are closer to the corresponding productivity frontier, we take as explanatory variable the interaction between trend labor productivity growth and a dummy variable equal to 1 if a state belongs to Group 1 (the set of states that are close to the technological frontier). More formally, we estimate the following equation:

$$Y_{it} = A + B_i + B_t + \beta_1 g_{it} + \beta_2 G_{it} + \beta_3 G_{it} * g_{it} + \beta_4 X_{it} + \gamma * t + \varepsilon_{it}, \tag{10}$$

where Y_{it} is the measure of inequality, B_i is a state fixed effect, B_t is a year fixed effect, G_{it} is the group dummy with a corresponding threshold h in terms of labor productivity (LP), g_{it} is the current labor productivity growth in region i at time t, $\gamma * t$ is a Census Division specific time trend and X is a vector of control variables.

In this equation, the effect of labor productivity growth on inequality is reflected by $\beta_1 + \beta_3$ for states above the productivity threshold and by β_1 for states below the threshold. In particular we want to know whether β_3 is statistically significant and whether $\beta_1 + \beta_3$ is positive.

4.1.2 Results

The regression results are shown in Table 2 and the relevant variables are defined in Table 2. In Table 2: Columns 1 to 3 show the OLS estimates for equation (10) in which states are assigned to Group 1 when their productivity is among the two highest quintiles (that is, belonging to the 20 most productive states in the year). Columns 4 to 6 present similar results with Group 1 involving states above the productivity median (and therefore belonging to the 25 most productive states in the year).

We find that frontier productivity growth is positively and significantly correlated with the top 1% income share. This is evidenced by the positive and significant interaction coefficient β_3, and this is robust to controlling for population growth, for the share of financial sector, for government size and for estimates of the output gap. Moreover, the interaction is sufficiently high that $\beta_1 + \beta_3$ is significantly positive (this is confirmed by a Student test). In other words, frontier productivity growth is positively correlated with the top 1% income. However, non frontier productivity growth is negatively correlated with the top 1% share as evidenced by the negative estimate for β_1. The effect of productivity growth on the top 10% income share is not significant at the 10% level; however the coefficient becomes significantly positive at the 10% level when Alaska is excluded.[14] In this case, the coefficient for frontier productivity growth when regressing the top 1% income share, is greater than the corresponding coefficient for the top 10%. In fact, a Student test shows that the equality of the two corresponding coefficients is always rejected.

We also checked the robustness of the effect of frontier productivity growth on income inequality to considering alternative and broader measure of inequality (Gini index, Atkinson Index, and Theil Index). For these two last measures (Atkinson and Theil, not shown) the correlations between frontier growth and inequality are insignificant, whether we use a 20 states or 25 states frontier threshold (i.e. a dummy equal to one for the 20 or 25 most productive states). Columns 3 and 6 of Table 2 show the results when using the Gini coefficient as left hand-side variable in the regression. The interaction term is not significant in both case. When Alaska is excluded, the interactive term is positive and highly significant, but not sufficiently high for $\beta_1 + \beta_3$ to be positive: in other words, the overall effect of frontier productivity growth on the Gini coefficient is negative. These results suggest that the productivity growth at the frontier affects inequality but only for very specific measures, concentrated at the top of the distribution.

Overall, our results suggest that the link between frontier growth and top incomes shares should be positive. However, in itself this does not suffice to establish a causal link from frontier-growth to top income inequality, as one can think of a number of potential omitted variables. For example, inflows of talented individuals from other states should increase both the top 1% share

[14] Alaska is the state with the highest level of labor productivity, which in turn is most likely due to both, its large oil sector and its small labor force.

(these individuals tend to have higher earnings) and productivity growth (these individuals are more productive). Product market or taxation reforms may also affect both top income shares and productivity growth. This leads us to turn our attention more specifically on the relationship between innovativeness and top income inequality.

4.2 The effect of innovativeness on top incomes

4.2.1 Estimation Strategy

We seek to look at the effect of innovativeness measured by the flow (number) 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 X% income share on our measures of innovativeness. Our estimated equation is:

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

where y_{it} is the measure of inequality, B_i is a region (i.e. country or state) fixed effect, B_t is a year fixed effect, $innov_{i(t-1)}$ is innovativeness in year $t-1$, and X is a vector of control variables.

As in the previous subsection, the control variables include the growth of total population, an estimate of the output gap, the size of the financial sector, the size of government and here we also add GDP per capita as a control.

4.2.2 Results from OLS regression

Table 3 presents the results from regressing top income shares and other inequality measures on the flow of patents. Once again, the relevant variables are defined in Table 1. As explained in the previous section, the number of patent granted by the USPTO for a given application date has been corrected for the truncation bias, which explains why the last year in the sample is 2009. In addition to what was already presented, we also control for the share of natural resources in the state GDP. With this control, we want to correct for undesirable fluctuations of the top 1% income share in states like Wyoming or West Virginia that can be directly attributed to this sector.

From Table 3 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. Besides, as expected, the later variable has a significant and negative effect on top income inequalities.

Table 4 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 2006, 2005 and 2004 respectively for these three measures.

The results from Table 4 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 that have been renewed at least one after having been issued per capita. In all instances, we find a positive and significant effect of innovation on the top 1% income share.

4.2.3 Other measures of inequality

In this section, we perform the same regressions as before but using other measures of inequality. At the cross state level, we have broader measures of inequality (some of them have already been used in the growth regressions): in particular, the Gini coefficient, the Atkinson index, the Theil index and the Relative Mean Deviation of the distribution of income. 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 addition to all these measures, we also have data on the top 10% 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 top2% 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.[15] Column 1 reproduces the results for the top 1% income share. Column 2 uses the *Avgtop* measure, column 3 uses the top10% 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 Index with parameter 0.5 and the Theil index. The effect of innovativeness is non significant for the Theil Index and significant at the 10% level for the Atkinson index.

Looking at column 2 of Table 6, we can see that the effect of innovativeness on the share of income received by the top 10 to top 2% of the income distribution

[15]We chose to present results for the 3 year window citation variable but results are the same for other measures of quality of innovation.

is not significant (and if anything, the coefficient is negative); however, as shown in column 3, the effect of innovativeness on the top 10% income share including the top 1% income share is positive. In other words, the positive effect of innovativeness on top incomes is due to the effect of innovativeness on the top 1% income share. Gini indexes (columns 4 and 5) show positive coefficients, yet not significant. Interestingly, the coefficient for the bottom 99% Gini is negative and significant, suggesting once again that all the positive effect of innovativeness on the income distribution inequality is concentrated at the very top of the income distribution.

Together, these results strongly suggest that the link between innovativeness and income inequality is mainly driven by what happens at the very top of the income distribution, and specifically at the top 1% income share, which in turn is consistent with the Schumpeterian view underlying our model. In return, these broader measures of income inequality are likely to be more affected by the *direction* of innovation instead of the *rate* of innovation.

4.2.4 Instrumentation

To deal with potential endogeneity issues, we instrument for innovativeness in the regression of top income on innovativeness. We try different instrumentation strategies. A first variable we consider as a potential instrument is *Educ*, the number of students enrolled in higher education over total population at time $t-5$. This *Educ* variable turns out to be a reasonably good instrument, with an F statistics at 111.8, and it shows a positive and significant effects both for top 1% and top 10% income shares in second stage regressions (not presented here). Yet the use of *Educ* as instrumental variable, can be criticized for being itself too "endogenous". To deal with this concern, we consider two other instruments.

First, following Aghion et al (2004), 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).[16] The rationale for using this instrument is analyzed at length in Aghion et al. (2004): in a nutshell, the appropriation committees allocate federal funds to research education across US states.[17]

[16] 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 appointment date and termination date.

[17] 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): "In the U.S. Senate and House of Representatives, the Appropriations Committees control the allocation of federal funds to projects. Some funds for research universities are awarded through a competitive process whereby the Appropriations Committees simply allocate a lump sum to an agency like the National Science Foundation and have it disburse the money using merit-based competitions. However, the Appropriations Committees can also propose that individual projects be funded without regard to merit or

A member of Congress who sits in such a Committee often push 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. What makes the State composition of Appropriation Committees a potentially good instrument for research education subsidies and thus for innovativeness, is the fact that what determines changes in the State-composition of the appropriation committees in the Senate or the House of Representatives, has little to do with growth or innovation performance in those states: it has more to do with random events such as the death or retirement of current heads or other members of these committees, combined with the need to maintain a fair distribution of seats between Democrats and Republicans and also across US states representatives.

Two interesting remarks are worth making at this point. First, 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. Second, the fact that a congressman is appointed to the committee is only the result of a complicated political process in which politicians compare seniority and influence to choose the most suitable candidate. For these reasons, 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 (an decrease in θ or β in the context of our model).

Based on these Appropriation Committee data, different instruments for innovativeness 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.[18]

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.* (2004), many politicians in the

larger policy considerations. It is well known that such individual projects are the main route by which congressmen deliver payback to their constituents. It is precisely the opportunity to fund such projects that makes a seat on the Appropriations Committee so valuable.

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. While a legislator can also direct money to an array of other types of projects, these do not add up to much money compared to research and infrastructure funding". This explains why the Appropriation Committee variable is a good instrument for reearch education in Aghion et al (2009), and why it also makes sense to use it as an instrument for innovativeness here.

[18]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., 2004), and another one which only consider 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).

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 year, 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 committee 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. As described above, the appropriation committee allocate federal funds mostly through two important channels: research universities and infrastructure (mainly highways). Because of this second channel, one can imagine a situation in which the owner of a construction company will capture part of these funds to accumulate wealth. 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 this issue, we use data on federal allocation to states by identifying the sources of state revenue (see Aghion et al., 2009). Such data can be found at the Census Bureau from before 1950 on a yearly basis. We compute the amount of state revenue from the federal government aimed at buildings and maintaining highways (denoted highways and given in real 2010 US dollars per inhabitant) and control for the logarithm of this variable in the regression. Subsequently, we drop the size of government from the control variable. Finally, we exclude the District of Columbia (DC) from the dataset because of the absence of representatives from this juridiction in the Senate.

Our results for the effect of innovativeness on the top 1% income share in the corresponding IV regressions are shown in Table 7. 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. All these results are available upon request.

Columns 1 to 3 show the effect of the number of citations in a 3 year windows per capita on top 1% income share (variable *3YWindow*) while columns 4 to 6 use the number of patents in the 5% most cited (variable *Share5*)[19] this effect is positive and significant whether we consider 1, 2 or 3 year lags, except for column (6) where the effect if significant only at the 11% level. First stage regression F-statistics are reported at the bottom of Table 7.

Finally, 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 relative innovation spillovers from these other states. 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

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

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 1975 to 1984. 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, whose application date is t, to a patent of state j, and if $innov(j,t)$ denotes our measure of innovativeness in state j at time t, then we posit:

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

where T is the length of the period (1975-1984) used to compute the weights $w_{i,j}$ and Y is the instrument.[20] Table 8 presents the results when the logarithm of Y 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.

Overall, our two instrumentation strategies[21], based respectively on the appropriation committee composition and on cross-state innovation spillovers, suggest a causal link from innovativeness and the top 1% income share. The same is true when we use these same instruments when regressing other (broader) measures of income inequality on innovativeness. In particular, when the spillover based instrument is used, the regression coefficient of Avgtop on innovativeness becomes significantly negative, in line with the view that the positive effect of innovation on income inequality is concentrated on the very top of the income distribution.

4.2.5 The role of two specific sectors: finance and energy

When considering top income shares and other inequality measures on the one hand and innovativeness on the other hand, we did not look at industry composition in the various states. However, two particular sectors deserve to be considered more closely: Finance and Oil extraction. Indeed, 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

[20] Interestingly, the weights $w_{i,j}$ are not correlated with the distance between states. Consequently, with this measure we do not capture geographical effect of spillover that could be seen as endogenous as well.

[21] When the two instruments are used together, the effect of innovativeness on the top 1% income share is still 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 Hansen test is used.

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 financial sector in state GDP.

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

Yet, 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. Results from regressing the top 1% income share on innovativeness as measured by the number of citations per capita (except for column 3 where we use the number of patent corrected from patent of class 705), are presented in Table 9, columns 1, 2 and 3. Data on employee compensation come from the BEA. 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 to 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. We divide patent application 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 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 9) should capture a variation in innovativeness 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 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 in Table 4

Next, we wish to address the possibility that our results be driven by the oil sector, in particular in a state like Alaska where oil extraction activities account for almost 30% of total GDP in 2009. With such a large share of the oil sector in state GDP, the top 1% income share is likely to involve individuals employed by the oil extraction sector, which in turn is highly sensitive to energy prices fluctuation. To deal with this concern, we perform two tests: first, we add the share of oil extraction related activities in state GDP as a control variable; 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 9. Here again, our results remain significant.[22]

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

More specifically, we use data from the NBER TAXSIM website.[23] 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 9[24] and shows that the effect of innovativeness instrumented by the Senate appropriation committee composition on the top 1% income share remains positive and significant.

4.2.7 Magnitude of the effects

The above results suggest a causal link from innovativeness to top income shares at the cross states level. At this stage it is worth setting back and looking at the magnitude of this effect. First, let us compare the effect of innovativeness on top income shares with the effect of the financial sector size, as measured by the variable *Sharefinance*. From Tables 3 and 4, we compare the effect on the top 1% of an increase in one standard deviation from our innovativeness measure with the effect of an increase in one standard deviation from the financial control variable. When the number of patents per thousand people is used as our measure of innovativeness, the effect of innovativeness accounts for 80% of the effect of financial development. But when our quality measures of innovativeness are used, the effect of innovativeness on top income shares becomes stronger than the effect of financial sector size. For example, an increase by one standard deviation in the number of patents among the 5 percent most cited patents per thousand people has an effect more than twice stronger than that of the financial variable. The effect is even bigger when looking at citations counts (whether it is a global count of within a 3, 4 or 5 year window) and can account for half the negative effect of the government size.

Next, we look at cross sectional differences across states in a given year in terms of our innovativeness measure. Our regressions suggest that if a state were to move from the first quartile of the distribution of patents per capita

[22]These results are also true when other measures of innovativeness are used.
[23]http://users.nber.org/ taxsim/state-tax-tables/
[24]Results are similar when other marginal tax rates are used as controls.

in 2000[25] to the fourth quartile, its top 1% income share would increase on average by 4.7 percentage points. For the sake of comparison, 4.7 percentage points is the difference in the top 1% income shares between California (26.2%) and Washington (21.5%). Results are comparable when using other measures of innovativeness: for example, if we use the number of citations, the difference is 4.4 percentage points. Similarly, when we restrict attention to states above the productivity median in 2000, the average difference between the first and fourth labor productivity growth quartiles in term of top income shares differences is 2.3 percentage points.

4.2.8 Quality of inventors and top income shares

Some innovators are particularly talented and therefore more likely to increase the revenues of their firm and thereby either enter the top 1% themselves or help the top management enter the top 1% (in terms of our model such innovators may be able to perform innovations with a 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 Scientists" in each state and in each year. Following Moretti and Wilson (2014), a star scientist is defined as an inventor who is among the top 5% most prolific inventor according to the number of patents they own in the past 5 years.[26] USPTO database, combined with the work of Lai et al. (2003), allows us to look at inventors for each patents granted from 1975 to 2010. Star scientists show very prolific innovation patterns, for example, Chris Land, an inventor from San Jose, CA, has participated in 40 patents from 2001 to 2005.

We aggregate this measure at the state level by computing the number of Star Scientists per capita in each state and each year. Then we use our instrument on Appropriation Committee membership to conduct a 2SLS regressions on top income shares. The regression is the same as previously; in particular, the District of Columbia is excluded and the instrument is the number of senators from each state on the Appropriation Committee (we also control for federal spending on infrastructure). Results are presented in Table 10 and show a positive and significant relationship between the number of star patentors and the top 1% income share. The corresponding first stage F-Stat is close but over 10 in each specification.

5 Discussion and extensions

In this section we extend our core analysis in four directions: first, we show the robustness of our core results to moving from cross-state to cross-CZ analysis; second, having moved to CZ-level analysis we consider the relationship between

[25] We chose 2000 as a reference year because it is the last year for which we have non corrected patents data. Result are consistent when this year changes

[26] We also check the same measure with 10 years, showing similar results.

innovativeness and social mobility; third, when analyzing the relationship between innovativeness and top incomes or social mobility, 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 Robustness to moving from State-level 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 (2015)'s Equality of Opportunity Project.[27] 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, the Equality of Opportunity Project uses 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.* (2011) to complete the USPTO database as we did when looking at star scientists. This enables us to associate each assignee with his address. To allocate a patent to a CZ, we use the 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. The size of government is proxied by local government expenditures per capita from the Equality of Opportunity Project.

Using all these data, we can first check whether the effects of innovation on the top 1% income share and on the Gini index are consistent with our cross-states findings. Table 5 displays the results from the regression when the logarithm of the number of patents per capita is used as a measure of innovation. We add controls for GDP per capita, for the growth of total population and for the size of local government proxied by the logarithm of the local government's total expenditure per capita. Standard errors are clustered by state to account for potential correlation across neighboring CZs. As seen from the first two columns of Table 5, the effect of innovativeness on the top 1% income share

[27] http://www.equality-of-opportunity.org/index.php/faq-s

is positive and significant (column 1) and robust to the addition of a dummy equal to one if the CZ belongs to urban areas (column 2). When regressing innovativeness on inequality as measured by the Gini coefficient and on the Gini coefficient for the bottom 99% of the income distribution, the coefficients are always negative. The effect is not significant for the overall Gini but highly significant for the bottom 99% Gini (columns 3 to 6).

All these observations are consistent with our core results at the cross state level.

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 affect 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 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. Finally, we drop CZ where no patent had been granted since 2006.

If we focus on the 50 largest commuting zones in our sample and sort them by the probability for a child to reach the highest quintile when the child's parents belonged to the lowest quintile, we find that the top 10 CZs in term of upward mobility at the top include: San Jose, San Diego, San Francisco, Seattle, New York, Boston, Sacramento and Los Angeles. These cities, most of them located in California, are among the most innovative in the US. At the other end of the spectrum, we find CZs like Charlotte, Memphis or Atlanta with a very small amount of patents per capita.

We thus conduct the following regression:

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

where Mob is our measure of upward social mobility, and $innov$ is our measure of innovativeness (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 involving around 570 CZs. Columns 1 and 2 look at the effect of innovativeness on upward mobility when the percentile of parent income is respectively 25 and 50. In both cases, the effect of innovativeness is positive and significant. Columns 3 to 6 show our results for upward mobility at the top. That is, the probability for a child to belong to the highest quintile in income distribution at the age 30 when his parent belonged to a lower quintile (1 for column 3, 2 for column 4, 3 for column 5 and 4 for column 6). In all cases, innovativeness shows a positive and significant correlation with upward mobility at the top except for the transition between the 4^{th} and the 5^{th} quintiles. In addition, we can see that the effect is stronger when parents belonged to a lower quintile. Finally, column 7 shows the overall effect of innovativeness on upward mobility when upward mobility is measured by the probability to reach the highest quintile when parent belonged to any lower quintile.

One concern is worth mentioning here: in some CZs, the size of the top quintile is very 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 7 of previous regressions.[28].

All the results presented in this section are consistent with the prediction of our model that innovativeness increases mobility at the top.

5.3 New entrant versus incumbent innovation

Our empirical results have highlighted 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 "new entrant patent" if the time lag between its application date and the first patent application date of the same assignee is less than 3 years. We then aggregate the number of "new entrant patents" as well as the number of "incumbent patents" at the state level from 1979 to 2009[29] and at the CZ level by averaging between 2006 and 2010.

We first focus on the effect of new entrant innovation on social mobility. We thus conduct the same regression as in the previous section at the cross CZ level but considering separately new entrant innovation and incumbent innovation on the right hand side of the regression equation. Table 12 presents our results. Columns 1 to 3 regress our three measures of social mobility on the number of "new entrant patents" per capita, whereas columns 4 to 6 regress the three

[28] 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 size higher than 15% of total CZ population. The coefficient for this interaction term is positive and significant.

[29] We start in 1979 to reduce the risk of wrongly considering a patent to be new 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).

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.

We now look at the effect of new entrants' innovation on top income inequality, making full use of our panel data and instrumenting at the cross-state level. Following our definition of new entrant innovation, almost 19% of patent applications from 1980 to 2009 can be considered "new". These "new" patents have on average 50% more citations than incumbent patents, confirming the intuitive idea that new patents correspond to more radical innovations (see Akcigit and Kerr, 2010).

Table 13 presents the results from regressing the top 1% income share over three measures of innovativeness (number of patents per capita, number of citations per capita and number of citations made within a 3 year window per capita), respectively restricting attention to new entrant patents (columns 1, 3, and 5) and to incumbent patents (columns 2, 4, and 6). We instrument these innovativeness variables using the number of seats in the appropriation committee of the senate.[30] The coefficients on innovativeness are always positive and significant, whether innovativeness refers to incumbents' or entrants' innovation. When using the flow of patents per capita as innovativeness measure, the effect of entrant innovation is stronger than that of incumbent innovation (see columns 1 and 2). However, the two coefficients are essentially identical when using the number of citations per capita and the number of citations made within 3 years, which suggests that entrants' innovations have a bigger impact on top income inequality mainly because they tend to be more radical on average.

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.

Measuring lobbying expenditures at state or at CZ level is not straightforward. In particular, the OpenSecrets project[31] 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 for the state, as the weighted average of lobbying expenditure 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.

[30] We use the three year lag instrument because results are more significant with it, although using the 2 year lag instrument yields similar results.

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

We then define the lobbying intensity by sector k in state i as:

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

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.[32] We therefore move the analysis from CZ to MSA at this point and compute similar Bartik measures of lobbying intensity at that level (in particular the number of patents has been aggregated at zipcode level).

Our resulting measure of lobbying at state level places Mississippi, Arkansas and Wisconsin as the three states with the highest intensity of lobbying activities, defined as total lobbying expenditures over GDP. This intensity is negatively correlated with the ratio of new firms (defined as firm of age 0 from the Census Bureau) and with the number of patent application from new entrants. Thus, in states where lobbying intensity is stronger, new entrants seem to have more difficulties to innovate. Looking over time at states with lobbying intensity above the median, we find that this group remains quite stable. In fact, 23 states are in this group every year from 1998 to 2010 (and this is also true in 2011, 2012 and 2013). We define these states[33] as high lobbying intensity states and create a dummy equal to one whenever a state belongs to that group. We then interact this dummy with the logarithm of the number of patents per capita. Columns 1 and 2 of Table 14 shows the results respectively for the OLS (column 1) and for the IV (column 3) regressions of the top 1% income share on the total number of citations per capita (in log) and the interaction term between the dummy variable for high 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

[32] http://lehd.ces.census.gov/

[33] 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.

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.* (2015) who only provide absolute mobility data and no transition matrix. 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 349 MSAs which can be separated in two groups, 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 patent per capita (in log) on the logarithm of absolute upward mobility. We see that this effect is positive and significant only for MSA that are below median in terms of lobbying intensity.

To sum up, in line with our model, lobbying reduces the impact of innovativeness on social mobility and its impact on top 1% income share.

6 Conclusion

In this paper we have analyzed the effect of innovation-led growth on top incomes and on social mobility. Our results show positive and significant correlations between innovativeness or frontier growth on the one hand, and top income shares or social mobility on the other hand. Our instrumentation at cross-state level suggests that these correlations at least partly reflect a causality from innovativeness to top income shares. Moreover, we show the important role played by entrant innovation both on social mobility and on the top 1% share. This in turn vindicates the Schumpeterian view whereby the rise in top income shares in developed countries and particularly in the US over the past decades, is at least partly related to innovation-led frontier growth, where innovation itself can spur social mobility at the top through the process of creative destruction.

These findings suggest interesting avenues for further research on (innovation-led) growth, inequality and social mobility. A first avenue is to look at how income inequality affects individuals' ability to innovate.[34] A second avenue is to look in more details at countries like Finland, Sweden or Norway for which not only innovation and income data but also social mobility data are available over a much longer period than the US: in particular we want to look at the effects of the innovation-enhancing reforms (including product and labor market liberalization reforms and tax reforms) implemented in these countries in the early 1990s on top income shares, productivity growth/patenting, and social mobility. Did the reforms lead to an increase in all these variables simultaneously as our analysis would suggest? These and other extensions of the analysis in this paper are left for future research.

[34] Here we ought to mention ongoing work by Bell et al (2014).

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7 Appendix to section 2

In this Appendix we extend our analysis of the model to the case where incumbent also innovates, that is $\pi_H - \pi_L = 1/\eta_L - 1/\eta_H > \beta$, so that

$$\widetilde{x}^* = (\pi_H - \pi_L - \beta)/\theta,$$

which is decreasing in θ and β (therefore we assume that $> \beta$). The share of sectors with high mark-ups is given by (6),[35] therefore the innovation rate of entrants x^* solves

$$x^* = \frac{1}{\theta}\left(\left(\pi_H - \left[\frac{(1-z)\,x^* + \tilde{x}^*}{\eta_H} + \frac{1-((1-z)\,x^* + \tilde{x}^*)}{\eta_L}\right]\right)(1-z) - \beta\right),$$

which results in

$$x^* = \frac{\left(\pi_H - \frac{1}{\eta_H} + \left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)\tilde{x}^*\right)(1-z) - \beta}{\theta + (1-z)^2\left(\frac{1}{\eta_H} - \frac{1}{\eta_L}\right)},$$

since $\widetilde{x}^*$ is decreasing in β and θ, then so is x^* (recall that $\frac{1}{\eta_L} - \frac{1}{\eta_H} > 0$).[36]

The aggregate innovation rate is given by $x^* + \widetilde{x}^*$ (which is decreasing in θ and β) and the share of sectors with a high mark-up is given by:

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

which increases in the innovation rates of incumbents and entrants, but increases less with entrants' innovation the higher entry barriers are.

The equilibrium growth rate is now given by:

$$g^* = \eta_H^{\mu^*} - 1,$$

whereas the expressions for factor income shares become:

$$wage\_share_t = \frac{Lw_t}{Y_t} = \frac{\mu^*}{\eta_H} + \frac{1-\mu^*}{\eta_L}$$
$$entrepreneur\_share_t = \frac{Y_t - Lw_t}{Y_t} = 1 - \frac{\mu^*}{\eta_H} - \frac{1-\mu^*}{\eta_L}.$$

Finally, the probability that an offspring has the same occupation as her parent is still given by (8), so that social mobility is still proxied by:

$$1 - \Psi = (1-z)\,x^*.$$

which is decreasing in β and θ. Therefore the same logic as before applies and we get:

[35] A way to microfound that both the entrant and the incumbent cannot innovate at the same time is the following. Assume that every period there is a mass 1 of ideas, and only one idea is succesful. Research efforts 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 $x^* + \tilde{x}^* < 1$, which is satisfied for θ large enough.

[36] x^* increases with $\widetilde{x}^*$, because more innovation by incumbents lowers wages which decreases the opportunity cost of innovation for an entrant.

Proposition 2 *An increase in R&D productivity (that is a decline in β or θ) leads to more innovation, a larger entrepreneur income share and more social mobility. However, this effect is dampened when there are high-barriers to entry.*

Proof. The only claim we have not yet established is that $\frac{\partial^2}{\partial\theta\partial z}\mu^* > 0$ and $\frac{\partial^2}{\partial\beta\partial z}\mu^* > 0$ (which immediately implies that the positive impact of a increase in R&D productivity on growth, entrepreneur income share and social mobility is attenuated when barriers to entry are high).

To establish this latter claim, note that

$$\frac{\partial^2}{\partial\theta\partial z}\mu^* = \frac{\partial^2}{\partial\theta\partial z}(1-z)\,x^* \text{ and } \frac{\partial^2}{\partial\beta\partial z}\mu^* = \frac{\partial^2}{\partial\beta\partial z}(1-z)\,x^*.$$

Next, note that we have:

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

which is indeed increasing in z (as $\tilde{x}^*$ is independent of z and $\frac{\partial\tilde{x}^*}{\partial\theta} < 0$ and $\frac{1}{\eta_L}-\frac{1}{\eta_H} > 0$).

Similarly:

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

which is also increasing in z ($\frac{\partial\tilde{x}^*}{\partial\beta} < 0$). This establishes the proposition. ■

8 Tables

Variable Names	**Description**
	Measure of inequality
top01	Share of income own by the richest 0.1% (on a scale of 0 to 100).
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 technology
Group	Dummy equal to one if a state is above the productivity median.
GrowthLP	Growth rate of labor productivity.
	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, $i \in \{1, 2, 3, 4\}$.
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	Share of financial sector in total GDP.
Outputgap	Output gap.
Gvtsize	Share of government sector in total GDP.
NaturalRessources	Share of natural ressources in global GDP.

Table 1: Description of relevant variables used in regressions.

Measure of Inequality	(1) Top 1%	(2) Top 10%	(3) Gini	(4) Top 1%	(5) Top 10%	(6) Gini
*GrowthLP*Group*	21.992***	0.901	10.505	18.309***	1.188	9.831
	(3.21)	(0.08)	(0.65)	(2.81)	(0.12)	(0.71)
GrowthLP	-12.597**	-10.325*	-33.384***	-11.765*	-10.101*	-31.996***
	(-2.06)	(-1.93)	(-4.35)	(-1.95)	(-1.84)	(-3.87)
Group	0.026	0.318	0.033	0.063	0.402**	0.199
	(0.12)	(1.28)	(0.11)	(0.34)	(2.29)	(0.93)
Gvtsize	-0.038	-0.202**	0.085	-0.057	-0.179*	0.142**
	(-0.44)	(-2.35)	(1.09)	(-0.68)	(-1.99)	(2.34)
Popgrowth	7.435	6.827	-8.751	7.690	6.197	-11.195
	(0.73)	(0.62)	(-0.59)	(0.77)	(0.60)	(-0.78)
Outputgap	-0.619	-0.304	0.972	-1.099	-0.646	0.630
	(-0.75)	(-0.43)	(1.16)	(-1.17)	(-0.75)	(0.53)
ShareFinance	0.049	0.034	-0.028	0.047	0.037	-0.021
	(0.93)	(0.39)	(-0.34)	(0.90)	(0.41)	(-0.25)
R^2	0.910	0.938	0.895	0.910	0.939	0.896
N	1785	1785	1785	1785	1785	1785

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 2: Effect of the growth rate of productivity on inequality for two groups of US states. Three different measures of inequality are used: the share of income held by the richest 1%, the share of income held by richest 10% and the GINI index. Group is a dummy equal to one if a state is above the third quintile in term of productivity for columns 1 to 3 and above the median for columns 4 to 6. Time span:1975-2009. Ordinary Least Square regressions with robust standard errors. We include time and state fixed effects and Census Division specific time trend. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)
Measure of Inequality	Top 1%	Top 1%	Top 1%	Top 1%
Measure of Innovation	patent_pc	patent_pc	patent_pc	patent_pc
Innovation	0.024**	0.028**	0.030**	0.029**
	(2.04)	(2.09)	(2.14)	(2.13)
Gdppc		-0.088	-0.098	-0.133*
		(-1.18)	(-1.29)	(-1.76)
Popgrowth		-0.007	-0.010	-0.082
		(-0.01)	(-0.01)	(-0.08)
Sharefinance			0.002	0.002
			(0.70)	(0.75)
Outputgap			0.009	0.026
			(0.12)	(0.33)
Gvtsize				-0.004
				(-0.73)
NaturalRessources				0.003
				(0.15)
R^2	0.922	0.923	0.923	0.923
N	1734	1734	1734	1734

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 3: Effect of the logarithm of the number of patent per capita (corrected for truncation bias and lagged) on the logarithm of the top 1% income share. Time span: 1976-2009. 51 states. Panel data OLS regression with robust standard errors. State-fixed effect and time dummies are added but not reported. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Inequality	Top 1%	Top 1%	Top 1 %	Top 1%	Top 1%	Top 1%
Measure of Innovation	3YWindow	4YWindow	5YWindow	Citations	Share5	Renew
Innovation	0.032***	0.041***	0.042***	0.049***	0.026***	0.029**
	(3.85)	(3.63)	(3.14)	(3.29)	(3.28)	(2.31)
Gdppc	-0.143*	-0.158*	-0.183**	-0.163**	-0.145*	-0.233*
	(-1.87)	(-1.97)	(-2.06)	(-2.07)	(-1.70)	(-1.99)
Popgrowth	-0.229	-0.431	-0.550	-0.316	-0.559	0.636
	(-0.21)	(-0.39)	(-0.47)	(-0.29)	(-0.53)	(0.54)
Sharefinance	0.003	0.003	0.004	0.003	0.003	0.003
	(1.10)	(1.30)	(1.33)	(1.31)	(1.07)	(1.68)
Outputgap	0.023	0.054	0.072	0.033	0.127	0.132
	(0.25)	(0.58)	(0.82)	(0.35)	(1.50)	(1.00)
Gvtsize	-0.005	-0.007	-0.010**	-0.006	-0.006	-0.002
	(-1.02)	(-1.60)	(-2.17)	(-1.15)	(-1.16)	(-0.28)
NaturalRessources	0.003	0.002	0.002	0.002	0.006	0.016
	(0.15)	(0.12)	(0.12)	(0.12)	(0.27)	(0.67)
R^2	0.920	0.915	0.908	0.921	0.930	0.884
N	1632	1581	1530	1632	1559	1483

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 4: Effect of different measures of the quality of innovation (in log, lagged) on the logarithm of the top 1% income share. Time span: 1975-2006 for column (1), 1975-2005 for column (2), 1975-2004 for column (3), 1976-2006 for column (3), 1976-2006 for column (5) and 1982-2007 for column (6). 51 states. Panel data OLS regression with robust standard errors. State-fixed effect and time dummies are added but not reported. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Inequality	Top 1%	Top 1%	Gini	Gini	G99	G99
Measure of Innovation	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc
Innovation	0.186**	0.174*	-0.059	-0.073	-0.144**	-0.162**
	(2.25)	(1.97)	(-0.94)	(-1.13)	(-2.09)	(-2.34)
Gdppc	0.711***	0.625***	0.070	-0.019	-0.104	-0.226**
	(4.22)	(3.50)	(0.74)	(-0.20)	(-0.92)	(-2.09)
Gvtsize	-0.100*	-0.080	-0.066	-0.043	-0.071	-0.042
	(-1.89)	(-1.41)	(-1.38)	(-0.94)	(-1.27)	(-0.83)
Popgrowth	0.123***	0.107***	0.081***	0.063***	0.078***	0.055***
	(8.11)	(6.23)	(5.60)	(4.50)	(4.16)	(2.94)
R^2	0.277	0.287	0.158	0.197	0.168	0.227
N	607	607	611	611	607	607

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 5: Effect of innovativeness on inquality as measured by the share of income held by the top 1%, by the overall gini index and by the Gini index for the bottom 99% income distribution at the commuting zone level. The measure of innovation is the log of the average number of granted patents per capita whose application date is between 1996 and 2002. 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 a dummy equal to one if the CZ is an urban area. Cross sectional OLS regression with robust standard errors clustered by state. Variables descriptions are given in table 1 (Gvtsize stands for the log of local government expenditure per capita).

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Inequality	Top 1%	Avgtop	Top 10 %	Overall Gini	G99	Atkin
Measure of Innovation	3YWindow	3YWindow	3YWindow	3YWindow	3YWindow	3YWindow
Innovation	0.032***	-0.006	0.008**	-0.004	-0.012***	0.013*
	(3.85)	(-1.25)	(2.02)	(-1.33)	(-3.34)	(1.78)
Gdppc	-0.143*	0.071	0.035	0.005	0.008	0.126**
	(-1.87)	(1.49)	(1.43)	(0.21)	(0.25)	(2.63)
Popgrowth	-0.229	-0.543	-0.148	-0.494**	-0.656***	0.288
	(-0.21)	(-1.61)	(-0.57)	(-2.67)	(-3.58)	(0.93)
Sharefinance)	0.003	-0.001	0.001	-0.000	-0.001	0.002
	(1.10)	(-0.23)	(0.45)	(-0.36)	(-1.01)	(0.53)
Outputgap	0.023	-0.062	-0.061***	-0.010	-0.002	-0.100**
	(0.25)	(-1.09)	(-2.98)	(-0.55)	(-0.08)	(-2.24)
Gvtsize	-0.005	-0.004	-0.003*	0.002	0.003	-0.006*
	(-1.02)	(-1.23)	(-1.74)	(1.05)	(1.49)	(-1.71)
NaturalRessources	0.003	0.007	0.000	0.006	0.008*	-0.006
	(0.15)	(1.17)	(0.04)	(1.16)	(1.90)	(-0.43)
R^2	0.920	0.506	0.945	0.881	0.758	0.920
N	1632	1632	1632	1632	1632	1632

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 6: Regression of the 3 year window citation number (in log, 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 (see text for details), 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: 1975-2006. Panel data OLS regression with robust standard errors. State-fixed effect and time dummies are added but not reported. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Inequality	Top 1%	Top 1%	Top 1 %	Top 1%	Top 1%	Top 1%
Measure of Innovation	3YWindow	3YWindow	3YWindow	Share5	Share5	Share5
Innovation	0.144**	0.127**	0.163**	0.108**	0.082*	0.079
	(2.37)	(2.33)	(2.00)	(2.00)	(1.83)	(1.36)
Gdppc	-0.184**	-0.175**	-0.195**	-0.155*	-0.141*	-0.140
	(-2.11)	(-2.20)	(-2.16)	(-1.65)	(-1.69)	(-1.52)
Popgrowth	0.705	0.613	0.812	-0.336	-0.310	-0.307
	(0.94)	(0.83)	(1.04)	(-0.50)	(-0.48)	(-0.47)
Sharefinance	0.007**	0.006**	0.008**	0.006**	0.005*	0.005
	(2.33)	(2.37)	(2.12)	(1.97)	(1.88)	(1.42)
Outputgap	0.040	0.033	0.049	0.094	0.094	0.094
	(0.19)	(0.16)	(0.23)	(0.54)	(0.56)	(0.57)
NaturalRessources	-0.003	-0.001	-0.004	0.007	0.008	0.008
	(-0.40)	(-0.20)	(-0.52)	(1.01)	(1.11)	(1.14)
Highways	0.026**	0.024***	0.028**	0.017*	0.015*	0.014
	(2.47)	(2.58)	(2.14)	(1.85)	(1.86)	(1.54)
Lag of instrument	2 years	1 year	3 years	2 years	1 year	3 years
R^2	0.911	0.915	0.906	0.920	0.927	0.928
First stage F stat	21.70	27.44	15.02	14.31	21.24	10.08
N	1598	1598	1598	1598	1598	1598

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 7: Effect of innovativeness (in log, lagged) on inequality measured by the share of income held by the richest 1% (in log) IV panel regressions. Columns (1) to (3) test the effect on the number of patents per capita, columns (4) to (6) test the effect of one indicator of quality of innovation: the average number of citation made to a patent. Time span: 1975-2006. 2 SLS robust panel data regression with the number of seats occupied at the appropriation committee in the Senate used as an instrument for inovativeness. States-fixed effect and time dummies are added. Variables descriptions are given in table 1.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of Inequality	Top 1%	Top 1%	Top 1 %	Top 1%	Top 1%	Top 1%
Measure of Innovation	patent_pc	3YWindow	4YWindow	5YWindow	Citations	Share5
Innovation	0.145**	0.065***	0.114***	0.115***	0.132***	0.101***
	(2.39)	(2.69)	(2.98)	(2.93)	(2.87)	(2.81)
Gdppc	-0.194**	-0.144*	-0.164*	-0.198**	-0.207**	-0.178*
	(-2.37)	(-1.79)	(-1.94)	(-2.34)	(-2.50)	(-1.88)
Popgrowth	0.212	-0.220	-0.334	-0.439	-0.318	-0.605
	(0.29)	(-0.32)	(-0.46)	(-0.54)	(-0.46)	(-0.95)
Sharefinance	0.005**	0.004**	0.006***	0.007***	0.006***	0.007***
	(2.35)	(2.42)	(2.94)	(3.05)	(2.89)	(2.86)
Outputgap	0.088	0.050	0.100	0.127	0.086	0.148
	(0.46)	(0.25)	(0.47)	(0.59)	(0.44)	(0.82)
Gvtsize	-0.003	-0.002	-0.003	-0.006*	-0.004	-0.004
	(-0.97)	(-0.61)	(-1.02)	(-1.81)	(-1.11)	(-1.26)
NaturalRessources	-0.004	0.003	-0.000	0.000	-0.000	0.004
	(-0.49)	(0.43)	(-0.05)	(0.06)	(-0.07)	(0.61)
R^2	0.912	0.915	0.906	0.897	0.911	0.914
First stage F stat	34.04	92.10	43.97	46.30	40.04	24.49
N	1734	1581	1530	1479	1581	1510

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 8: Effect of different measures of the quality of innovation (in log) on the logarithm of the top 1% income share. IV panel regressions. Time span: 1976-2009 for column (1), 1976-2006 for column (2), 1976-2005 for column (6), 1976-2004 for column (4), 1976-2006 for column (5) and 1976-2006 for column (6). 51 states. 2 SLS robust panel data regression with the the spillover at time t-1 used as an instrumentused (see text for details) for inovativeness. States-fixed effect and time dummies are added. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure of Inequality	Top 1%	Top 1%	Top 1%	Top 1 %	Top 1%	Top 1%	Top 1%
Measure of Innovation	Citations	Citations	patent_pc	Citations	Citations	patent_pc	Citations
Innovation	0.135**	0.136**	0.188**	0.140**	0.138**	0.186**	0.153**
	(2.43)	(2.52)	(2.22)	(2.13)	(2.51)	(2.23)	(2.57)
Gdppc	-0.197**	-0.180**	-0.212**	-0.195**	-0.151*	-0.211**	-0.213**
	(-2.17)	(-1.99)	(-2.43)	(-2.31)	(-1.92)	(-2.43)	(-2.38)
Popgrowth	0.112	0.191	0.801	0.095	0.102	0.790	0.088
	(0.17)	(0.27)	(1.17)	(0.14)	(0.15)	(1.16)	(0.12)
Sharefinance	0.006***	0.006**	0.006**	0.006**	0.005**	0.006**	0.006**
	(2.59)	(2.29)	(2.15)	(2.33)	(2.15)	(2.15)	(2.47)
Outputgap	0.039	0.054	0.053	0.035	-0.017	0.052	0.067
	(0.20)	(0.22)	(0.28)	(0.18)	(-0.09)	(0.28)	(0.34)
Highways	0.022**	0.017*	0.026***	0.022**	0.021**	0.026***	0.024***
	(2.48)	(1.94)	(2.69)	(2.50)	(2.36)	(2.69)	(2.63)
NaturalRessources	0.001	-0.001	-0.005	0.002	0.005	-0.005	0.002
	(0.16)	(-0.17)	(-0.72)	(0.35)	(0.68)	(-0.67)	(0.37)
RemunFinance	0.006						
	(0.14)						
EFD				-0.134			
				(-0.45)			
Oil					-0.006		
					(-1.59)		
Maginal Tax Rate							0.006**
							(2.08)
R^2	0.919	0.921	0.915	0.918	0.919	0.915	0.912
First stage F stat	32.03	28.47	24.62	24.36	33.41	25.21	29.04
N	1598	1470	1698	1598	1598	1698	1548

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 9: Effect of the number of patents per capita on the top 1% income share (in log, lagged). Variable *Oil* measures the share of oil related activities in GDP while variable *RemunFinance* measures the average compensation per employee in the financial sector and variabel *EFD* measures the financial dependence of innovation. Other variable definition are given in Table 1. In column (2), NY, CT, DE and SD are dropped from the dataset, in column (3), finance-related patents have been removed, in column (6), oil-related patent have been removed and in column (7) marginal tax rate of labor is added as a control. Time Span: 1975-2009 for columns (3) and (6), 1975-2007 for other columns. Panel data IV regression, innovativeness is instrumented by the number of seats in the Senate Appropriation Committee with a 2 year lag. State-fixed effect and time dummies are added but not reported.

Measure of Inequality	**(1)** Top 1%	**(2)** Top 1%	**(3)** Top 1%
Number of star scientists	0.148**	0.141*	0.161**
	(2.22)	(1.96)	(2.20)
Gdppc	-0.310**	-0.301**	-0.328**
	(-2.44)	(-2.42)	(-2.55)
Popgrowth	0.604	0.571	0.676
	(0.69)	(0.67)	(0.75)
Sharefinance	0.005**	0.005*	0.006**
	(1.99)	(1.93)	(2.02)
Outputgap	0.247	0.236	0.269
	(0.98)	(1.04)	(1.07)
NaturalRessources	-0.007	-0.007	-0.009
	(-0.78)	(-0.66)	(-0.85)
Highways	0.038**	0.037**	0.041**
	(2.48)	(2.19)	(2.50)
Lag of instrument	2 years	3 year	1 years
R^2	0.878	0.882	0.869
First stage F stat	10.89	10.06	10.40
N	1498	1498	1498

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 10: Effect of the number of top scientists per capita (in log, lagged) on the logarithm of the top 1% income shares. Time span: 1977-2006. Panel data 2SLS IV regression with the number of senators on the Appropriation Committee used as an instrument for the number of star scientists. States-fixed effect and time dummies are added. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Measure of Mobility	AM25	AM50	P1-5	P2-5	P3-5	P4-5	P5
Measure of Innovativeness	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc
Innovation	1.365***	0.853**	0.012***	0.011***	0.009**	0.002	0.007**
	(3.13)	(2.40)	(3.46)	(2.81)	(2.55)	(0.49)	(2.18)
Gdppc	-1.290	-0.435	-0.021	-0.009	-0.022	-0.007	0.021
	(-0.56)	(-0.23)	(-1.17)	(-0.46)	(-1.18)	(-0.30)	(1.04)
Gvtsize	3.435**	2.074	0.028**	0.028**	0.024*	0.007	0.021
	(2.25)	(1.62)	(2.61)	(2.14)	(1.87)	(0.52)	(1.63)
Popgrowth	-1.429**	-1.633***	-0.008*	-0.012**	-0.018***	-0.021***	-0.016***
	(-2.61)	(-3.66)	(-1.95)	(-2.60)	(-3.94)	(-4.77)	(-3.42)
R^2	0.152	0.166	0.136	0.124	0.144	0.129	0.152
N	567	567	573	573	573	573	573

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 11: Effect of innovativeness on social mobility at the commuting zone level. Columns (1) and (2) test the effect of the number of patents per capita on absolute upward mobility when the parent percentile is set to 25 and 50. Columns (3) to (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 column (3), 2 for column (4), 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 regression with standard error clustered by state, a dummy variable equal to one if the CZ belong to an urban area is added but not reported. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Mobility	AM25	P1-5	P2-5	AM25	P1-5	P2-5
Measure of Innovativeness	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc	patent_pc
	New Entrant patents			Incumbant patents		
Innovation	0.624**	0.006**	0.006**	0.568	0.004	0.005
	(2.06)	(2.37)	(2.15)	(1.25)	(1.15)	(1.10)
Gdppc	4.360	0.024	0.032	3.620	0.020	0.028
	(1.67)	(1.21)	(1.43)	(1.35)	(0.89)	(1.17)
Gvtsize	2.862**	0.025***	0.023**	2.854**	0.025**	0.024*
	(2.20)	(2.86)	(2.03)	(2.05)	(2.48)	(2.00)
Popgrowth	-0.795	-0.003	-0.008*	-0.665	-0.002	-0.007
	(-1.61)	(-0.80)	(-1.74)	(-1.30)	(-0.37)	(-1.40)
R^2	0.230	0.205	0.181	0.211	0.183	0.167
N	546	551	551	532	573	573

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

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 "new entrant patents" while columns (4) to (6) focus on "incumbant patents". Cross-Section OLS regression with standard error clustered by state, a dummy variable equal to one if the CZ belong to an urban area is added but not reported. Variables descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Inequality	top 1%	top 1%	top 1%	top 1%	top 1%	top 1%
Measure of Innovativeness	patent_pc	patent_pc	Citations	Citations	3YWindow	3YWindow
Origin of innovation	new	incumbant	new	incumbant	new	incumbant
Innovation	0.393*	0.230**	0.138**	0.094**	0.114**	0.106**
	(1.74)	(2.04)	(2.05)	(2.30)	(2.24)	(2.26)
Gdppc	-0.462***	-0.228*	-0.346***	-0.270**	-0.482***	-0.397***
	(-3.03)	(-1.79)	(-3.50)	(-2.19)	(-3.96)	(-3.23)
Popgrowth	1.562	1.227	0.777	0.234	0.874	1.145
	(1.58)	(1.24)	(0.87)	(0.22)	(1.09)	(1.24)
Sharefinance	-0.000	0.008**	0.003	0.005***	0.002	0.008***
	(-0.13)	(2.44)	(1.12)	(2.71)	(0.90)	(2.95)
Outputgap	0.524	-0.075	0.220	0.035	0.312	0.139
	(1.62)	(-0.25)	(0.83)	(0.11)	(1.22)	(0.47)
NaturalRessources	0.021**	-0.011	0.018*	0.012	0.015	0.006
	(2.08)	(-0.71)	(1.77)	(1.41)	(1.58)	(0.53)
Highways	0.057**	0.041***	0.023**	0.026**	0.028**	0.035**
	(2.41)	(2.58)	(2.10)	(2.22)	(2.34)	(2.32)
Lag of instrument	3 years	3 years	3 years	3 years	3 years	3 years
R^2	0.695	0.806	0.790	0.841	0.821	0.830
First state F stat	6.4 8	11.17	9.42	19.29	14.83	16.43
N	1523	1526	1374	1374	1374	1374

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 13: Effect of innovativeness (in log) on inequality measured by the share of income held by the richest 1% (in log). IV panel regressions with the number of seat from the Senate Appropriation Committee used to instrument innovation measure (3 year lag). Columns (1), (3) and (5) restrict the sample on new entrant patents and columns (2), (4) and (6) focus on incumbant patents. States fixed effect and time dummmies are added. Variable descriptions are given in table 1.

	(1)	(2)	(3)	(4)	(5)
Measure of Inequality	top 1%	top1%	top 1%	-	-
Measure of Innovativeness	Citations	Citations	Citations	patent_pc	patent_pc
Origin of innovation	All	New Entrant / Incumbant	All	All	
Measure of Mobility	-	-	-	AM25	AM25
Innovation	0.092***	0.027*** / 0.008	0.175***	0.009	0.008*
	(4.65)	(4.30) / (0.73)	(5.35)	(1.11)	(1.76)
*Above Median Lobbying * Innovation*	-0.087**	-0.033*** / -0.015	-0.110***		
	(-4.68)	(-4.36) / (-1.16)	(-5.35)		
Gdppc	-0.128	-0.249	-0.156**	0.038	0.025
	(-1.52)	(-1.44)	(-1.99)	(1.40)	(0.72)
Popgrowth	-0.363	0.297	-0.387	2.560	0.268
	(-0.36)	(0.30)	(-0.56)	(1.59)	(0.23)
Sharefinance	0.003	0.002	0.005***	0.001	-0.003**
	(1.22)	(0.81)	(2.72)	(0.48)	(-2.34)
Outputgap	0.005	0.166	0.051		
	(0.07)	(1.57)	(0.27)		
Gvtsize	-0.004	-0.003	-0.002	-0.001	0.001
	(-0.85)	(-0.50)	(-0.80)	(-0.43)	(0.81)
NaturalRessources	0.004	0.015	0.002		
	(0.22)	(0.63)	(0.34)		
R^2	0.927	0.889	0.919	0.104	0.056
First stage F stat	-	-	28.41	-	-
N	1632	1376	1632	172	176

Notes: $***pvalue < 0.01$. $**pvalue < 0.05$. $*pvalue < 0.10$.
t/z statistics in brackets, computed with robust standard errors

Table 14: Effect of innovativeness (in log and lagged) on inequality and social mobility, breakdown using lobbying intensity. Column (1) presents results from an OLS regression at the cross state level for every patent citations while Column (2) use new Entrant patents and incumbant separately (in a OLS horse-race regression). Column (3) use the measure of spillover as an instrument variable. Both regression used a panel data with a time span 1975-2006 and 1976-2006 with time dummies and states fixed effect. Columns (4) and (5) present results from an OLS regression at the cross-MSA level with robust standard errors clustered at the state level. Column (3) restrict the sample to MSA that are above median in terms of lobbying activity and column (4) focus on MSA below this median. Variable descriptions are given in table 1.

9 Figures

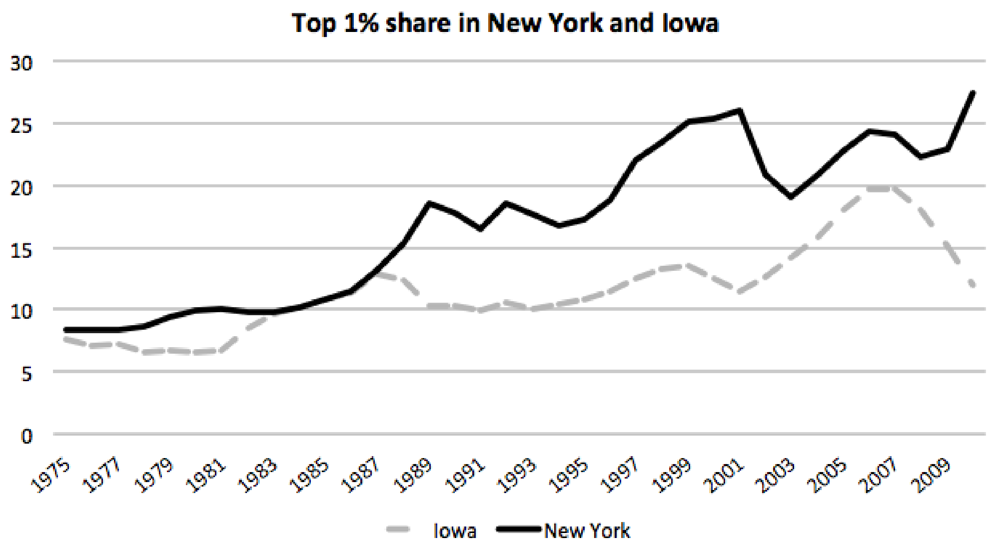

Figure 1: Evolution of top 1% income share in New York and in Iowa

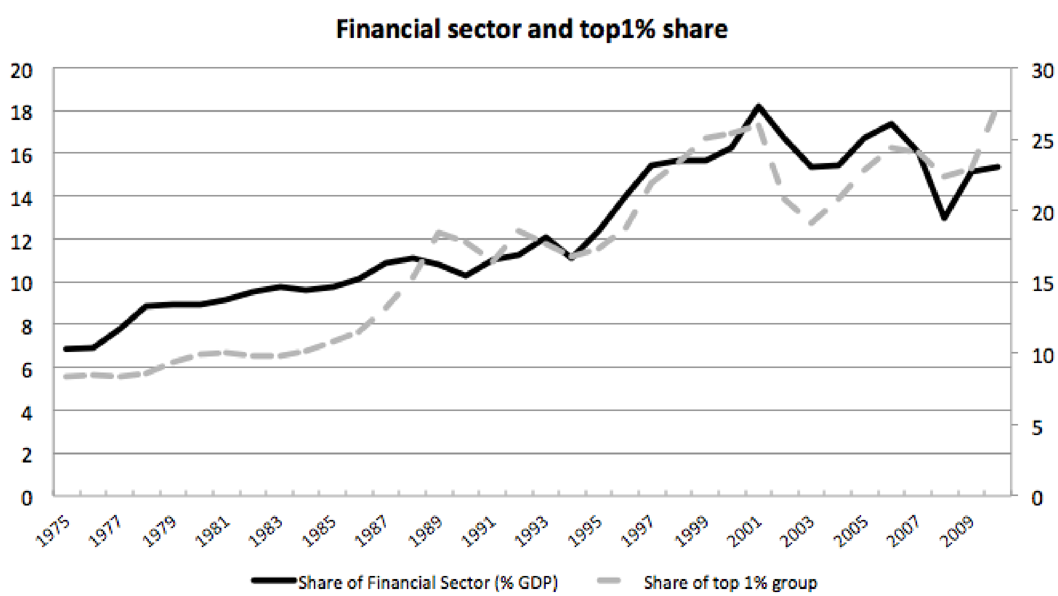

Figure 2: Evolution of the share of financial sector and on the top 1% share in the state of New York