Innovation and Top Income Inequality*

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Abstract

In this paper we use cross-state panel and cross US commuting-zone data to look at the relationship between innovation, top income inequality and social mobility. We find positive correlations between measures of innovation and top income inequality. We also show that the correlations between innovation and broad measures of inequality are not significant. Next, using instrumental variable analysis, we argue that these correlations at least partly reflect a causality from innovation to top income shares. Finally, we show that innovation, particularly by new entrants, is positively associated with social mobility, but less so in local areas with more intense lobbying activities.

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

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1 Introduction

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

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

More closely related to our analysis in this paper, Figure 2 looks at the relationship between the increase in the log of innovation in a state between 1980 and 2005 (measured here by the number of citations within five years after patent application per inhabitant in the state) and the increase in the share of income held by the top 1% in that state over the same period. We see a clearly positive correlation between these two variables.

That the recent evolution of top income inequality should partly relate to innovation, should not come as a surprise. Indeed, if the increase in top income inequality has been pervasive across occupations, it has, in particular affected occupations that appear to be closely related to innovation such as being entrepreneurs, engineers, scientists but also managers.[3]

In a first part of the paper we develop a Schumpeterian growth model where growth results from quality-improving innovations that can be made in each sector either from the incumbent in the sector or from potential entrants. Facilitating innovation or entry increases the entrepreneurial share of income and spurs social mobility through creative destruction

[1]The worldwide interest for income and wealth inequality, has been spurred by popular books such as Goldin and Katz (2008), Deaton (2013) and Piketty (2014). The sharp increase in top income inequality in the United States over the past decades was documented by Piketty and Saez (2003).

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

[3]Bakija (2008) find that the income share of the top 1% in the US as a whole has increased by 11.2 percentage points between 1979 and 2005, out of this amount, 1.02 percentage points (that is 9.1% of the total increase) accrued to engineers, scientists and entrepreneurs. Yet, innovation also affects the income of managers and CEOs (Balkin, 2001; Frydman and Papanikolaou, 2015), and firm owners (Aghion *et al.*, 2015).

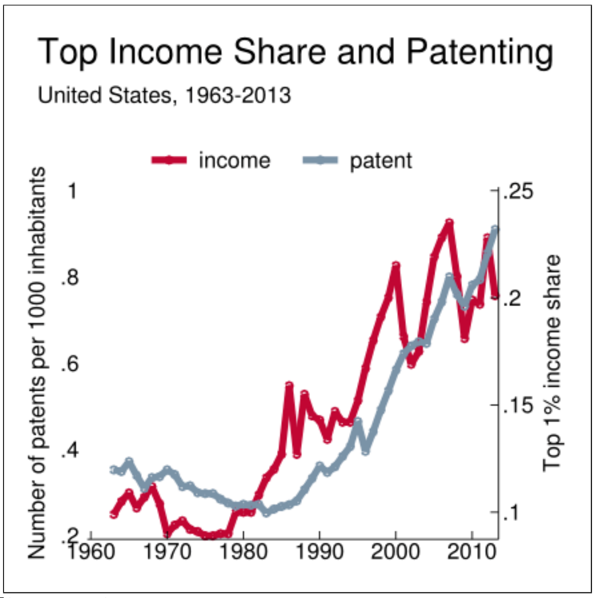

Figure 1: This figure plots the number of patent applications per 1000 inhabitant against the top 1% income share for the USA as a whole. Observations span the years 1963-2013. For more detail about the data, see section 3

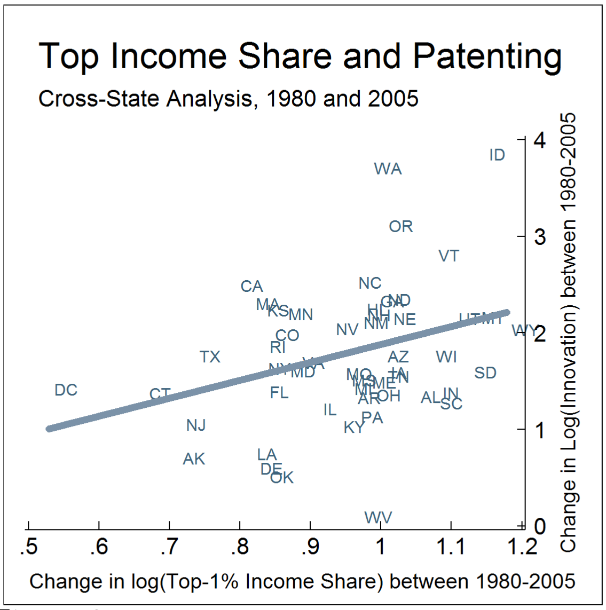

Figure 2: This figure plots the difference of the log of the number of citations per capita against the difference of the log of the top 1% income share in 1980 and 2005. Observations are computed at the US state level.

as employees' children more easily become business owners and vice versa. In particular, this model predicts that: (i) innovation by entrants and incumbents increases top income inequality; (ii) innovation by entrants increases social mobility; (iii) entry barriers lower the positive effects of entrants' innovations on top income inequality and social mobility.[4] Our model also shows that a higher level of mark-ups for an incumbent who has failed to innovate can lead to higher top income inequality and lower innovation; this higher mark-up level may in turn reflect slow diffusion of new technologies and/or high entry barriers.

We then start our empirical analysis by exploring correlations between innovation and various measures of inequality using OLS regressions. Our main findings can be summarized as follows. First, the top 1% income share in a given US state in a given year, is positively and significantly correlated with the state's degree of innovation, measured either by the flow of patents or by the quality-adjusted amount of innovation in this state in that year, as reflected by citations. Second, we find that innovation is less positively or even negatively correlated with measures of inequality which do not emphasize the very top incomes, or broader measures of inequality like the Gini coefficient, as suggested by Figure 3 below.[5]

[4] In Appendix A.3 we extend the model to show how innovation can affect at the same time CEO pay, scientists' pay and capital owners' income.

[5] Figure 3 plots the average top-1% income share and the bottom 99% Gini index as a function of their

Next, looking at the relationship between inequality and innovation at various lags, we find that the correlation between innovation and the top 1% income share is temporary. Finally, we find that the correlation between innovation and top income inequality is dampened in states with higher lobbying intensity.

Next, we argue that the correlation between innovation and top inequality at least partly reflects a causal effect of innovation-led growth on top incomes. We instrument for innovation using data on the appropriation committees of the Senate (following Aghion *et al.*, 2009). We find that all the broad OLS results in Section 4 are confirmed by the corresponding IV regressions. Our IV coefficient implies that an increase of 1% in the number of patents per capita increases the top 1% income share by 0.24% and that the effects of a 1% increase in the citation-based measures are of comparable magnitude. This means for example that in California where the flow of patents per capita has been multiplied by 3.1 and the top 1% income share has been multiplied by 2.4 from 1980 to 2005, the increase in innovation can explain 30% of the increase in the top 1% income share over that period. On average across US states, the increase in innovation as measured by the number of patents per capita explains about 22% of the total increase in the top 1% income share over the period between 1980 and 2005.

Looking at cross state differences in a given year, we can compare the effect of innovation with that of other significant variables such as the importance of the financial sector. Our IV regression suggests that if a state were to move from the first quartile in terms of the number of patents per capita in 2005 to the fourth quartile, its top 1% income share would increase on average by 3.5 percentage points. By comparison, moving from the first quartile in terms of the size of the importance of the financial sector to the fourth quartile, would lead to a 4.5-percentage-point increase in the top 1% income share.

Our results pass a number of robustness tests. First, we add a second instrument for innovation in each state which relies on knowledge spillovers from the other states. We show that when the two instruments are used jointly, the overidentification test does not reject the null hypothesis that the instruments are uncorrelated with the error term. In other words, we do not reject the validity of the instruments. Second, we show that the positive and significant correlation between innovation and top income shares in cross state panel regressions, is robust to introducing various proxies reflecting the importance of the financial sector and to controlling for sectors' size or for potential agglomeration effects.

Finally, when looking at the relationship between innovation and social mobility, using

corresponding innovation percentiles. The bottom 99% Gini is the Gini coefficient when the top 1% of the income distribution is removed. Innovation percentiles are computed using the US state-year pairs from 1975 to 2010. Each series is normalized by its value in the lowest innovation percentile.

cross-section regressions performed at the commuting zone (CZ) level, we find that: (i) innovation is positively correlated with upward social mobility (Figure 4 below[6]); (ii) the positive correlation between innovation and social mobility, is driven mainly by entrant innovators and less so by incumbent innovators, and it is dampened in MSAs with higher lobbying intensity.

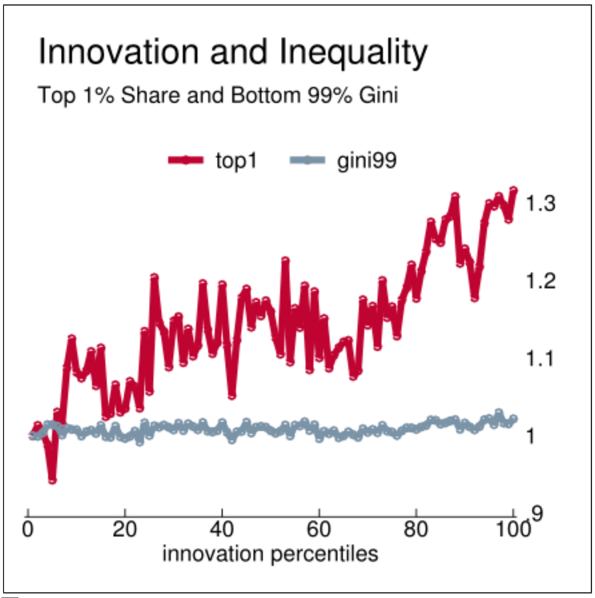

Figure 3: See footnote 5 for explanations.

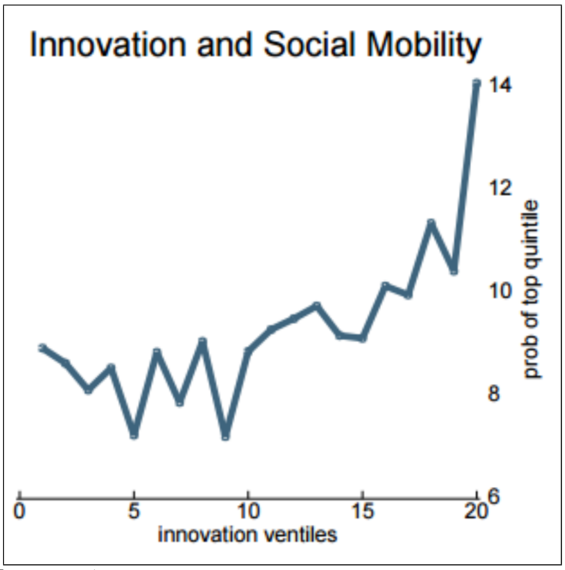

Figure 4: See footnote 6 for explanations.

The analysis in this paper relates to several strands of literature. First, to the endogenous growth literature (Romer, 1990; Aghion and Howitt, 1992). We contribute to this literature, by introducing social mobility into the picture and linking it to creative destruction, and by looking explicitly at the effects of innovation on top income shares.[7]

Second, to an empirical literature on inequality and growth (see for instance Barro, 2000 which studies the link between overall growth and inequality measured by the Gini coefficient; see also Forbes, 2000, and Banerjee and Duflo, 2003). 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. We contribute to this literature by showing that innovation-led growth is a source of top income inequality.

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

[7]Hassler and Rodriguez-Clare (2000) analyze the relationship between growth and intergenerational mobility in a model which may feature multiple equilibria, some with high growth and high social mobility and others with low growth and low social mobility. In that paper however, growth is driven by externalities instead of resulting from innovations.

Third, a large literature on skill-biased technical change aims at explaining the increase in labor income inequality since the 1970's.[8] While this literature focuses on the *direction* of innovation and on broad measures of labor income inequality (such as the skill-premium), our paper is more directly concerned with the rise of the top 1% and how it relates with the *rate* and *quality* of innovation (in fact our results suggest that innovation does not have a strong impact on broad measures of inequality compared to its impact on top income shares).

Fourth, our paper relates to a recently active literature on inequality and firm dynamics. Thus Rosen (1981) emphasizes the link between the rise of superstars and market integration: namely, as markets become more integrated, more productive firms can capture a larger income share, which translates into higher income for its owners and managers. Similarly, Gabaix and Landier (2008) show that the increase in the size of some firms can account for the increase in their CEO's pay. Song *et al.* (2015) show that most of the rise in earnings inequality can be explained by the rise in across-firm inequality rather than within-firm inequality. 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 and pay.[9]

Fifth, our analysis relates to a recent literature on innovation and income mobility. Thus Frydman and Papanikolaou (2015) find that innovation and executive pay are positively correlated at the firm level, but that pay inequality across executives and between executives and workers increases with innovation. Similarly, Balkin (2001) finds that innovation increases CEO pay in high-tech industries. Aghion *et al.* (2015) use individual income and patenting data from Finland to show that innovation increases an individual innovator's probability to make it to the higher income brackets, and that innovation has an even larger effect on firm owners' income. Bell *et al.* (2015) find that the most successful innovators see a sharp rise in income. Akcigit *et al.* (2016) merge historical census and patenting data across US states over the past 150 years and find a positive correlation between patenting intensity and social mobility.[10]

[8] 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. Lloyd-Ellis (1999) and Acemoglu (1998, 2002, 2007) see the skill distribution as determining the direction of technological change, while Hemous and Olsen (2014) argue that the incentive to automate low-skill tasks naturally increases as an economy develops. Several papers (Aghion and Howitt, 1998; Caselli, 1999 and Aghion *et al.*, 2002) see General Purpose Technologies (GPT) as lying behind the increase in inequality, as the arrival of a GPT favors workers who adapt faster to the detriment of the rest of the population. Krusell *et al.* (2000) show how with capital-skill complementarity, the increase in the equipment stock can account for the increase in the skill premium.

[9] Our analysis is also consistent with Hall *et al.* (2005), Blundell *et al.* (1999) or Bloom and Van Reenen (2000) who find that innovation has a positive impact on market value.

[10] Gabaix *et al.* (2016) argue that standard models of individual income dynamics, which are built on random growth, cannot quantitatively account for the increase in income inequality because they generate

Most closely related to our paper is Jones and Kim (2014), who also develop a Schumpeterian model to explain the dynamics of top income inequality. In their model, growth results from both, the accumulation of experience or knowledge by incumbents (which may in turn result from incumbent innovation) and creative destruction by entrants. The former increases top income inequality whereas the latter reduces it by allowing entrants to catch up with incumbents.[11] In our model instead, a new (entrant) innovation increases mark-ups in the corresponding sector, whereas in the absence of a new innovation, mark-ups are partly eroded as a result of imitation. On the other hand, the two papers have in common the ideas: (i) that innovation and creative destruction are key factors in the dynamics of top income inequality; (ii) that fostering entrant innovation contributes to making growth more "inclusive".[12]

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 innovation. Section 4 presents our OLS regression results. Section 5 presents our IV results. Section 6 performs robustness tests. Section 7 looks at the relationship between innovation and social mobility. Section 8 concludes. The main tables (Table 1 to Table 16) are displayed at the end of the main text. The Online Appendix A contains the theoretical proofs. And the Online Appendix B displays the additional tables (Tables B1 to B12).

2 Theory

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

transitional dynamics that are too slow. Instead, they suggest a model where some agents have a higher mean growth rate. This literature and our paper highlight that such a higher mean could result from innovation.

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

[12] Indeed, we show that entrant innovation is positively associated with social mobility. Moreover, if, as we shall see below, incumbent innovation and entrant innovation contribute to a comparable extent to increasing the top 1% income share, additional regressions shown in Appendix (see Table B1) suggest that incumbent innovation contributes more to increasing the top 0.1% share than entrant innovation (and even more for the top 0.01% share).

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 $L + 1$ of individuals in the economy, a mass 1 are capital owners who own the firms and the rest of the population works as production workers (with $L \geq 1$). Each individual lives only for one period. Every period, a new generation of individuals is born and individuals that are born to current firm owners inherit the firm from their parents. The rest of the population works in production unless they successfully innovate and replace incumbents' children.

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 labor productivity. Each intermediate i is produced by a monopolist who faces a competitive fringe from the previous technology in that sector.

2.1.2 Innovation

Whenever there is a new innovation in any sector i in period t, quality in that sector improves by a multiplicative term $\eta_H > 1$ so that:

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

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

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

Overall, the technological lead enjoyed by the incumbent producer in any sector i takes two values: η_H in periods with innovation and $\eta_L < \eta_H$ in periods without innovation.[13]

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

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

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

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

In this model, we measure upward social mobility by the probability Ψ_t that the offspring of a worker becomes a business owner. This in turn happens only if this individual gets to be a potential entrant and then manages to innovate and to avoid the entry barrier captured by z.

2.1.3 Timing of events

Each period unfolds as follows:

1. In each line i where an innovation occurred in the previous period, followers copy the corresponding technology so that the technological lead of the incumbent shrinks to η_L.

2. In each line i, a single potential entrant is drawn from the mass of workers' offsprings and spends $C_{E,t}(x_{E,i})$ and the offspring of the incumbent in sector i spends $C_{I,t}(x_{I,i})$.

3. With probability $(1-z)\, x_{E,i}$ the entrant succeeds, replaces the incumbent and obtains a technological lead η_H, with probability $x_{I,i}$ the incumbent succeeds and improves its technological lead from η_L to η_H, with probability $1-(1-z)\, x_{E,i} - x_{I,i}$, there is no successful innovation and the incumbent stays the leader with a technological lead of η_L.[14]

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

[14] For simplicity, we rule out the possibility that both agents innovate in the same period, so that in a given sector, innovations by the incumbent and the entrant are not independent events. This can be microfounded in the following way. Assume that every period there is a mass 1 of ideas, and only one idea is successful.

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

2.2 Solving the model

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

2.2.1 Income shares and social mobility for given innovation rates

In this subsection we assume that in all sectors, potential entrants innovate at some exogenous rate x_{Et} and incumbents innovate at some exogenous rate x_{It} at date t.

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

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

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

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

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

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

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

This, together with (3) and (2), allows us to immediately express the labor demand and the equilibrium profit in any sector i at date t. Labor demand by producer i at time t is given by:

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

Research efforts x_E and x_I 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 $x_E^* + x_I^* < 1$, which is satisfied for θ_K sufficiently large.

Equilibrium profits in sector i at time t are equal to:

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

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

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

We can now derive the expressions for the income shares of workers and entrepreneurs and for the rate of upward social mobility. Let μ_t denote the fraction of high-mark-up sectors (i.e. with $\eta_{it} = \eta_H$) at date t. Labor market clearing at date t implies that:

$$L = \int_0^1 l_{it} di = \int_0^1 \frac{Y_t}{w_t \eta_{it}} di = \frac{Y_t}{w_t} \left[\frac{\mu_t}{\eta_H} + \frac{1 - \mu_t}{\eta_L} \right]$$

We restrict attention to the case where $\eta_L - 1 > 1/L$, which ensures that regardless of the equilibrium value of μ_t,

$$w_t < \Pi_{L,t},$$

so that top incomes are earned by entrepreneurs. As a result, the entrepreneur share of income is a proxy for top income inequality (defined as the share of income that goes to the top earners—not as inequality within top-earners).

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

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

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

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

This entrepreneur share is "gross" in the sense that it does not take into account any potential monetary costs of innovation (and similarly all our share measures are expressed as functions of total output and not of net income—see below for the net shares).

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

$$\mu_t = x_{It} + (1 - z)\, x_{Et}, \tag{7}$$

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

Finally, recall that we measure upward social mobility by the probability Ψ_t that the offspring of a worker becomes a business owner. We have:

$$\Psi_t = x_{Et}\,(1 - z)\,/L, \tag{8}$$

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

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

Remark: That the equilibrium *share* of wage income in total income decreases with the fraction of high mark-up sectors μ_t, and therefore with the innovation intensities of entrants and incumbents, does not imply that the equilibrium *level* of wages also declines. In fact the opposite occurs.[15] In addition, note that the entrepreneurial share is independent of innovation intensities in previous periods. Therefore, a temporary increase in current innovation only leads to a temporary increase in the entrepreneurial share: once imitation

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

$$w_t = Q_t / \left(\eta_H^{\mu_t} \eta_L^{1-\mu_t} \right), \tag{9}$$

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

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

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

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

This last equation shows that the overall effect of an increase in innovation intensities is to increase the contemporaneous equilibrium wage, even though it also shifts some income share towards entrepreneurs.

occurs, the gains from the current burst in innovation will be equally shared by workers and entrepreneurs.[16]

2.2.2 Endogenous innovation

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

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

This expression states that the offspring of an incumbent can already collect the profits of the firm that she inherited ($\pi_L Y_t$), but also has the chance of making higher profit ($\pi_H Y_t$) by innovating with probability x_I. Clearly the optimal innovation decision is simply

$$x_{I,t} = x_I^* = \frac{\pi_H - \pi_L}{\theta_I} = \left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)\frac{1}{\theta_I}, \tag{11}$$

which decreases with incumbent R&D cost parameter θ_I.

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

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

since a new entrant chooses its innovation rate with the outside option being a production worker who receives wage w_t. Using equation (5), taking first order conditions, and using our assumption that $w_t < \pi_L Y_t$, we can express the entrant innovation rate as

$$x_{E,t} = x_E^* = \left(\pi_H - \frac{1}{L}\left[\frac{\mu_t}{\eta_H} + \frac{1 - \mu_t}{\eta_L}\right]\right)\frac{(1 - z)}{\theta_E}, \tag{12}$$

which implies that entrants innovate in equilibrium since $\pi_H > \pi_L > w/Y$.

Since in equilibrium $\mu^* = x_I^* + (1 - z)\,x_E^*$, the equilibrium innovation rate for entrants is simply given by

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

Throughout this section, we implicitly assume that θ_I and θ_E are sufficiently large that

[16] Another interpretation of the decrease in social mobility which results from an increase in lobbying is that lobbying increases the persistence of innovation rents.

$x_E^* + x_I^* < 1$.

Therefore lower barriers to entry (i.e. a lower z) and less costly R&D for entrants (lower θ_E) both increase the entrants' innovation rate (as $1/\eta_L - 1/\eta_H > 0$). Less costly incumbent R&D also increases the entrant innovation rate since x_I^* is decreasing in θ_I.[17]

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

Finally, equation (8) immediately implies that a reduction in entrants' or incumbents' R&D costs increases social mobility but less so the higher the barriers to entry are. We have thus established (proof in Appendix A.1):

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

Remark*:* Here we are treating lobbying intensity z as a given. An alternative would have been to assume that at cost $\theta_Z \frac{z^2}{2}$ the incumbent firm can prevent entry with probability z, and take the cost parameter θ_Z as an inverse measure of lobbying intensity/entry barrier.

2.2.3 Entrepreneurial share of income net of innovation costs

So far we computed gross shares of income, ignoring innovation expenditures.[18] If we now discount these expenditures, the ratio between net entrepreneurial income and labor income

[17] x_E^* increases with x_I^* because more innovation by incumbents lowers the equilibrium wage which decreases the opportunity cost of innovation for an entrant. This general equilibrium effect rests on the assumption that incumbents and entrants cannot both innovate in the same period.

[18] Not factoring innovation costs in our computation of entrepreneur shares of income amounts to treating those as private utility costs. Also in practice entrepreneurial incomes are typically generated after the innovation costs are sunk, even though in our model we assume that innovation expenditures and entrepreneurial incomes occur within the same period.

can be written as:

$$\begin{aligned} rel\_net\_share &= \left(Entrepreneur\_share_t - \theta_E \frac{x_E^2}{2} - \theta_I \frac{x_I^2}{2}\right) / \left(\frac{w_t}{Y_t} L\right) \\ &= \left(\pi_L + \frac{\pi_H - \pi_L}{2} x_I^* + \left(\frac{\pi_H}{2} + \frac{w_t}{2Y_t} - \pi_L\right)(1-z)\, x_E^*\right) / \left(\frac{w_t}{Y_t} L\right) \end{aligned} \tag{14}$$

where we used (6), (7) and the equilibrium values (11) and (12). This expression shows that a higher rate of incumbent innovation will raise the net entrepreneur share of income, whereas a higher rate of entrant innovation will only raise the net entrepreneurial share of income if $\frac{1}{2}\pi_H + \frac{1}{2}\frac{w_t}{Y_t} - \pi_L > 0$ (which occurs in particular if $\pi_H > 2\pi_L$). This in turn relates to the creative destruction nature of entrant's innovation: a successful entrant gains $\pi_H Y_t - w_t$ by innovating but she destroys the rents $\pi_L Y_t$ of the incumbent. Formally, we can show (see Appendix A.1):

Proposition 3 *An increase in incumbent R&D productivity (lower θ_I) leads to an increase in the relative shares of net entrepreneurial income over labor income. An increase in entrant R&D productivity (lower θ_E) also leads to an increase in the relative shares of net entrepreneurial income over labor income whenever* $\frac{1}{2}\pi_H + \frac{1}{2}\frac{w_t}{Y_t} - \pi_L > 0$.

On the other hand, we find that when L is large and π_H is close enough to π_L, then an increase in the productivity of entrant R&D will shift income towards workers instead of entrepreneurs, and therefore will contribute to a reduction in inequality. This result is in the vein of Jones and Kim (2014).

2.2.4 Impact of mark-ups on innovation and inequality

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

More interestingly perhaps, a higher η_L increases the mark-up of non-innovators, and thereby increases the entrepreneur share for a given innovation rate (see (6) and recall that $(1-z)\, x^* + \tilde{x}^* < 1$). Yet, it decreases incumbents' innovation rate since their net reward from innovation is lower. In the special case where $\theta_I = \theta_E$ this leads to a decrease in the total innovation rate (see Appendix A.2). For a sufficiently high R&D cost (θ high), the overall impact on the entrepreneur share remains positive. Therefore a higher η_L can contribute to a negative correlation between innovation and the entrepreneur share.

2.2.5 Shared rents from innovation

In the model so far, all the rents from innovation accrue to an individual entrepreneur who fully owns her firm. In reality though, the returns from innovation are shared among several actors (inventors, developers, the firm's CEO, financiers,...—see Aghion and Tirole, 1994, for a theoretical model of the relationship between inventors and developers and financiers of an innovation; Hall *et al.* (2005) show empirically that innovation increases firm value; and Balkin (2001) or Frydman and Papanikolaou (2015) show that innovation increases executives pay). We show this formally in Appendix A.3 where we extend our analysis, first to the case where the innovation process involves an inventor and a CEO, second to the case where the inventor is distinct from the firm's owner(s). Our theoretical results are robust to these extensions.

2.3 Predictions

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

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

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

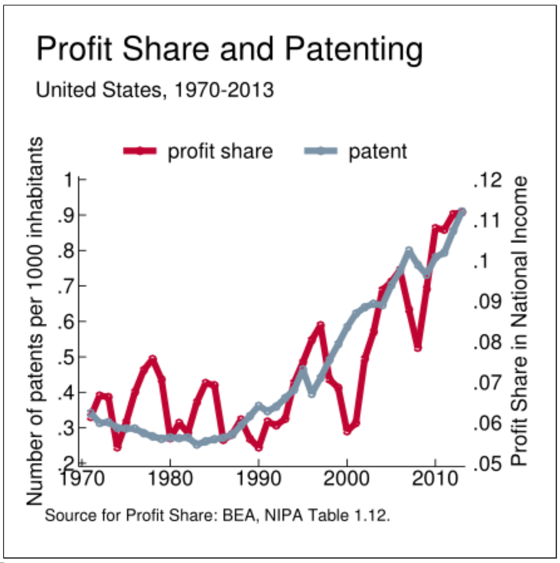

Figure 5: Profit Share in National Income

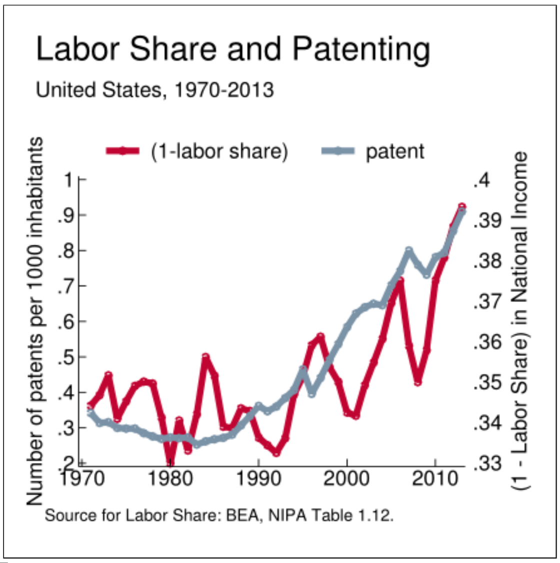

Figure 6: Labor Share in National Income

3 The empirical framework

In this section we present our measures of inequality and innovation and the databases used to compute these measures. Then we describe our estimation strategy.

3.1 Data and measurement

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

3.1.1 Inequality

The data on the share of income owned by the top 1% of the income distribution for our cross-US-state panel analysis, are drawn from the updated Frank-Sommeiller-Price Series from the US State-Level Income Inequality Database (Frank, 2009). From the same data source, we also gather information on alternative measures of inequality: namely, the top 0.01, 0.1, 0.5, 5 and 10% income shares, the Atkinson Index (with a coefficient of 0.5), the Theil Index and the Gini Index. These data are available from 1916 to 2013 but we restrict attention to the period after 1975. We end up with a balanced panel of 51 states (we include Alaska and Hawaii and count the District of Columbia as a "state") over a maximum time period of 36 years. In 2013, the three states with the highest share of total income earned by the richest 1% are New-York, Connecticut, and Wyoming with respectively 31.8%, 30.8% and 29.6% whereas Iowa, Hawaii and Alaska are the states with the lowest share earned by the top 1% (respectively 11.7%, 11.4% and 11.1%). In every US state, the top 1% income share has increased between 1975 and 2013, the unweighted mean value was around 8.4% in 1975 and reached 20.4% in 2007 before slowly decreasing to 17.1% in 2013. 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 coefficient of variation multiplied by 2.2 between 1975 and 2013. The states that experienced the fastest growth in the top 1% income share during the considered time period are Wyoming, Idaho, Montana and South Dakota; on the other hand DC, Connecticut, New Jersey and Arkansas experienced the lowest growth in that share.

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, 2014), allows us to assess the composition of the top 1% income share. On average between 1975 and 2013, wage income represented 59.3% and entrepreneurial income 22.8% of the total income earned by the top 1%, while for the top 10%, wage income represented 76.9% and entrepreneurial income 12.9% of total income. In our baseline model, entrepreneurs are those directly benefiting 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% (as highlighted in Appendix A.3). Yet, the fact that entrepreneurial income is over-represented in the top 1% income relative to wage income, suggests that our baseline model captures an important aspect in the evolution of top income inequality.

3.1.2 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 2014. For each patent, it provides information on the state of residence of the patent *inventor*, the date of application of the patent and a link to every citing patent granted before 2014. This citation network between patents enables us to construct several estimates for the quality of innovation as described below. Since a patent can be associated with more than one inventor and since coauthors of a given patent do not necessarily live in the same state, we assume that patents are split evenly between inventors and thus we attribute only a fraction of the patent to each inventor. A patent is also associated with an *assignee* that owns the right to the patent.

Usually, the assignee is the firm employing the inventor, and for independent inventors the assignee and the inventor are the same person. We chose to locate each patent according to the US state where its inventor lives and works. Although the inventor's location might occasionally differ from the assignee's location, most of the time the two locations coincide (the correlation between the two is above 92%).[19] Finally, in line with the patenting literature, we focus on "utility patents" which cover 90% of all patents at the USPTO.[20]

We associate a patent with its year of application which corresponds to the year when the provisional application is considered to be complete by the USPTO and a filing date is set. However, we only consider patents that were ultimately granted by 2014. For that reason, our data suffer from a truncation bias due to the time lag between application and grant. The USPTO considered in the end of 2012 that a patent application should be considered to be 95% complete for applications filed in 2004.[21] By the same logic, we consider that by the end of 2014, our patent data are essentially complete up to 2006. For the remaining years between 2006 and 2009, we correct for truncation bias using the distribution of time lags between the application and granting dates to extrapolate the number of patents by states following Hall *et al.* (2001). The small number of observed patents after 2009 led us to stop the correction in that year.

The annual flow of patent has been multiplied by 2.2 on average between 1975 and 2009. More than 70% of that increase is due to an increase in the number of inventors and 30% is due to an increase in the number of patents per inventor. Yet, simply counting the number of patents granted by their application date is a crude measure of innovation as it does not differentiate between a patent that made a significant contribution to science and a more incremental one. However, the USPTO database, provides sufficiently exhaustive information on patent citation to compute indicators which better measure the quality of innovation. We consider five measures of innovation quality.

- *5-year window citations counter*: this variable measures the number of citations received within no more than 5 years after the application date. This number has been

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

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

[21] 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."*

corrected to account for different propensity to cite across sectors and across time. In addition, because of the drop in the number of observed completed patents in the patent data after 2006, we need to correct for the truncation bias in citations. We did so by following Hall *et al.* (2001). We consider that the 5-year citation counter series is reliable up to 2006.

- *Is the patent among the 5% (resp. 1%) most cited in the year* according to the previous measure? This is a dummy variable equal to one if the patent applied for in a given year belong to the top 5% (resp. 1%) most cited patents in the next five years following its publication. Because this measure is based on the number of citations within a 5-year window, the corresponding series is stopped in 2006. A rational for using this measure, as argued in Abrams *et al.* (2013), has to do with the existence of potential non-linearities between the value of a patent and the number of forward citations.

- *Patent breadth*, defined as the number of claims in a patent. As argued in Akcigit *et al.* (2015), it is common to use patent claims to proxy for patent breadth. See also Lerner (1994).

- A weighted count of patents based on *generality*. We base our definition of patent generality on the 4-digit International Patent Classification (IPC) following the definition in Hall *et al.* (2001). Generality of a patent is taken to be equal to one minus the Herfindahl index from all the technological classes that cite the patent. Formally, the generality index G_{it} of a patent i whose application date is t is equal to:

$$G_{it} = 1 - \sum_{j=1}^{J} \left(\frac{s_{j,t,t+5}}{\sum_{j=1}^{J} s_{j,t,t+5}} \right)^2 ,$$

  where $s_{j,t,t+5}$ is the number of citations received from other patents in ICP class $j \in \{1..J\}$ within five years after t. If the citing patent is associated with more than one technology class, we include all these classes to compute the generality index.

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 year and then divided by the population in the state. These different measures of innovation 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 5-year window citation counts, and similarly for the four most innovative states between 1990 and 2010 (California, New York, Massachusetts and Texas). From Figure 2, those states which experienced the fastest growth in innovation are Idaho, Washington, Oregon and Vermont; on the other hand, the states with the lowest growth in innovation are West Virginia, Oklahoma, Delaware and Arkansas. More statistics are given in Tables 1 and 2.

3.1.3 Control variables

When regressing top income shares on innovation, a few concerns may be raised. First, the state-specific business cycle is likely to have direct effects on innovation and on top income share. Second, top income share groups are likely to involve to a significant extent individuals employed by the financial sector (see for example Philippon and Reshef, 2012, or Bell, 2014). In turn, the financial sector is sensitive to business cycles and it may also affect innovation directly. To address these two concerns, we control for the business cycle via the unemployment rate and for the share of GDP accounted for by the financial sector per inhabitant. In addition, we control for the size of the government sector which may also affect both top income inequality and innovation. To these we add usual controls, namely GDP per capita and the growth of total population. The corresponding data, namely on GDP, unemployment, total population and the share of the financial and public sectors, can be found in the Bureau of Economic Analysis (BEA) regional accounts.[22]

3.2 Estimation strategy

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

$$\log(y_{it}) = A + B_i + B_t + \beta_1 \log(innov_{i(t-2)}) + \beta_2 X_{it} + \varepsilon_{it}, \tag{15}$$

where y_{it} is the measure of inequality (which enters in log), B_i is a state fixed effect, B_t is a year fixed effect, $innov_{i(t-2)}$ is innovation in year $t-2$ (which enters in log as well),[23] and X is a vector of control variables. We discuss further dynamic aspects of our data later in the text. By including state and time fixed effects, we are eliminating permanent cross state differences in inequality and also aggregate changes in inequality.[24] We are essentially

[22]Data description is given in Table 3.

[23]When $innov$ is equal to 0, computing $\log(innov)$ would result in removing the observation from the panel. In such cases, we proceed as in Blundell (1995) and replace $\log(innov)$ by 0 and add a dummy equal to one if $innov$ is equal to 0. This dummy is not reported.

[24]We note that, after removing state and time effects, the inequality and innovation series are both stationary. For example, when we regress the log of the top 1% income share on its lagged value we find a precisely estimated coefficient of .821. Similarly when we regress innovation measured by citations in a

studying the relationship between the differential growth in innovation across states with the differential growth in inequality. In addition, by taking the log in both innovation and inequality, the coefficient β_1 can then be seen as the elasticity of inequality with respect to innovation.

Since we are using two-year lagged innovation on the right-hand side of the regression equation, and given what we said previously regarding the truncation bias towards the end of the sample period, we were able to run the regressions corresponding to equation (15) for t between 1977 and 2011 when measuring innovation by the number of patents and from 1977 and 2008 when measuring innovation using the quality-adjusted measures.

In all our regressions, we compute autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. By examining the estimated residual autocorrelations for each of the states we find that there is no significant autocorrelation after two lags. For this reason we choose a bandwidth equal to 2 years in the Newey-West standard errors.[25]

4 Results from OLS regressions

In this section we present the results from OLS regressions of top income and other measures of inequality on innovation. We first look at the correlation between innovation and top income inequality. Then we look at the correlations between top income and other measures of inequality. Next, we look at how top income inequality correlates with innovation at different lags. Then we look at how the correlation between innovation and top income inequality is affected by the intensity of lobbying, and finally we look at the relationship between innovation and entrant versus incumbent innovation.

4.1 Innovation and top income inequality

Table 4 regresses the top 1% income share on our measures of innovation. The relevant variables are defined in Table 3. Column 1 uses the number of patents as a measure of innovation, column 2 uses the number of citations in a 5 year window, column 3 uses the number of claims, column 4 uses the generality weighted patent count and columns 5 and 6 use the number of patents among the top 5% and top 1% most cited patents in the year. All these values are divided by the population in the state, taken in log and lagged by 2 years.

5-year window, on its one year lagged value, we find a precisely estimated coefficient of .779.

[25] The limited residual autocorrelation and the length of the time series (T is roughly equal to 30) justifies the use of a Newey-West estimator but we also present the main OLS regressions with clustered standard errors in Table B2 in Appendix B.

From Table 4 we see that the coefficient of innovation is always positive and significant at the cross state level except when we use the number of patents per capita (column 1). This in turn suggests that particularly the more highly cited patents are associated with the top 1%, as those are more likely to protect true innovations. This is in line with Hall *et al.* (2005) who show that an extra citation increases the market share of the firm which owns the patent. Finally, the positive coefficient on the relative size of the financial sector reflects the fact that the top 1% involves a disproportionate share of the population working in that sector.

Moreover, we can compare the magnitude of this correlation with the correlation between the top 1% income share and the importance of the financial sector: thus a one standard deviation increase in our measure of innovation is associated with a 0.037 point increase in the log of the top 1% income share whereas a one standard deviation increase in the share of financial sector in total GDP is associated with a 0.020 point increase in the log of the top 1% income share. Because the OLS estimates are likely to be biased, we refer the reader to section 5.1 for further discussion of the magnitude of our effects based on IV regressions.

4.2 Innovation and other measures of inequality

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

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

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

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

where top10 represents the size of the top 10% income share.

Table 5 shows the results obtained when regressing these other measures of inequalities on innovation quality. We chose to present results for the citation variable but results are similar when using other measures of innovation quality. Column 1 reproduces the results for the top 1% income share. Column 2 uses the *Avgtop* measure, column 3 uses the top 10% income share, column 4 uses the overall Gini coefficient and column 5 uses the Gini coefficient for the bottom 99% of the income distribution to measure income inequality on the left-hand side of the regression equation. Column 6 uses the Atkinson Index with parameter 0.5.

We see from Table 5 that innovation: (a) is most significantly correlated with the top 1% income share; (b) is less (but still) correlated with the top 10% income share or with the average share between 10% and 1%; (c) is not significantly correlated with the Gini index and is negatively correlated with the bottom 99% Gini (although this negative effect is small).[26] Moreover, the Atkinson index with coefficient equal 0.5 is positively correlated with innovation.

Finally, using new data recently released by Frank (2009), we were able to look at the effect of innovation on the very top of the income distribution, namely the top 0.01, 0.05 and 0.1% income shares. The correlation between innovation and top income share increased as we move up to the income distribution, with the coefficient of innovation reaching 0.065 for the top 0.01% income share. These results are presented in Table B3 of Appendix B.

4.3 Top income inequality and innovation at different time lags

One may first question the choice of two-year lag innovation in our baseline regression equation. In fact, two years is roughly the average time between a patent application and the date at which the patent is granted. For example, using Finnish individual data on patenting and wage income, Toivanen and Vaananen (2012) find an average lag of two years between patent application and patent grant, and they find an immediate jump in inventors' wages after patent grant. Other empirical results in two recent papers by Depalo (2014) and Bell *et al.* (2015) support the view that income can even peak before the patent is granted: Depalo (2014) find that inventors' wage peak around the time of the patent application, and Bell *et al.* (2015) show that the earnings of inventors start increasing before the filing date of the patent application. More generally, patent applications are mostly organized and supervised by firms who start paying for the financing and management of the innovation right after (or even before) the application date as they anticipate the future profits from the patent. Also, firms may sell a product embedding an innovation before the patent has been granted,

[26]This in turn may partly reflect the fact that, by concentrating market power within a few firms, innovation reallocates some rents from relatively high-earners towards very high-earners. For instance, in the context of our model, one could imagine that in the absence of innovation, a few firms behave as an oligopoly charging the mark-up η_L and dividing the profits among themselves. The owners of these firms would be high income earners but not necessarily in the top 1%. When innovation occurs, the leader captures all the rents and reaches the top 1% while the other individuals return to the production sector and see their income decline.

thereby already appropriating some of the profits from the innovation.

Table 6 shows results from regressing top income inequality on innovation at various lags. We let the time lag between the dependent variable and our measure of innovation vary from 2 to 6 years. We do not consider shorter time lags as we want to allow some time for innovation to generate income. In order to have comparable estimates based on a similar number of observations, we chose to restrict the time period to 1981-2008. From this table, we see that the effect of lagged innovation is significant up to three-years lags, but with more lags, the effect becomes insignificant. This latter finding is consistent with the view that innovation should have a temporary effect on top income inequality due to imitation and creative destruction, in line with the Schumpeterian model in Section 2.

4.4 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 innovation has lower effects on the top income share and on social mobility.

Measuring lobbying expenditures at the state level is not straightforward, in particular because lobbying activities often occur nationwide. To obtain a local measure of lobbying we use national sectoral variations in lobbying together with local variations in the sectoral composition in each state. More specifically, the OpenSecrets project[27] provides sector-specific lobbying expenditures at the national level for the period 1998-2011. To measure lobbying intensity at the state level, we construct for each state a Bartik variable, as the weighted average of lobbying expenditures in the different sectors (2-digits NAICS sectors), with weights corresponding to sector shares in the state's total employment from the US Census Bureau.

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

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

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

[27]Data can be found in the OpenSecrets website.

$1 \leq i \leq I$). From this we compute the aggregate lobbying intensity in state i as:

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

We then compute our measure of lobbying intensity by dividing the above measure of aggregate lobbying by the state population at year t. Table 7 shows the results from the OLS regression of the top 1% income share on innovation, our measure of lobbying intensity and the interaction between the two. Due to the limited time range for the lobbying data, we were able to run the regression only for the period 1998-2008. The results show that the overall effect of innovation on the top 1% income share is always positive and significant, the effect is weaker and even negative in states with higher lobbying intensity.

4.5 Entrants and incumbents innovation

Our empirical results so far have highlighted the positive relationship between innovation and top income inequality. In order to distinguish between incumbent and entrant innovation in our data, we rely on the work of Lai *et al.* (2014) which allows us to track the inventor(s) or assignee(s) for each patent over the period 1975-2010. We declare a patent to be an "entrant patent" if the time lag between its application date and the first patent application date of the same assignee amounts to less than 3 years.[28] We then aggregate the number of "entrant patents" as well as the number of "incumbent patents" at the state level from 1980 to 2010.[29]

According to our definition of an "entrant" innovation, 17% of patent applications from 1980 to 2010 correspond to an "entrant" innovation (this number increases up to 23.7% when we use the 5-year lag threshold to define entrant versus incumbent innovation). These "entrant" patents have more citations than the "incumbent" patents: for example in 1980, each entrant patent has 11.4 citations on average whereas an incumbent patent only has 9.5 citations, confirming the intuitive idea that entrant patents correspond to more radical innovations (see Akcigit, 2010).

[28] We checked the robustness of our results to using a 5-year lag instead of a 3-year lag threshold to define entrant versus incumbent innovation (see Table B4). Here, and only here, we only focus on patents issued by firms and we have removed patents from public research institutes or independent inventors.

[29] We start in 1980 to reduce the risk of wrongly considering a patent to be an "entrant" patent just because of the truncation issue at the beginning of the time period. In addition, we consider every patent from the USPTO database, including those with application year before 1975 (but which were granted after 1975).

Table 8 presents the results from the regression of the top 1% income share over incumbent and entrant innovation, where these are respectively measured by the number of patents per capita in columns 1, 2 and 3 and by the number of citations per capita in columns 4 to 6. The coefficients on entrant innovation are always positive and significant, and in the horse race regressions of top inequality on incumbent and entrant innovation (columns 3 and 6), only the coefficients for entrant innovation come out significant although the difference between the coefficients for entrant and incumbent innovation are not statistically significant.[30]

4.6 Summary

The OLS regressions of innovation on income inequality performed in this section lead to interesting correlation results that are broadly in line with the Schumpeterian view developed in the model, namely: (i) innovation is positively correlated with top income inequality; (ii) innovation is not significantly correlated with broader measures of inequality (Gini,...); (iii) the correlation between innovation and top income inequality is temporary (lagged innovation ceases to be significant when the lag becomes sufficiently large); (iv) the correlation between innovation and top income inequality is lower in states with higher lobbying intensity; (v) top income inequality is positively correlated with both, entrant and incumbent innovation.

5 Endogeneity of innovation and IV results

In this section we argue that the positive correlations between innovation and top income inequality uncovered in the previous section, at least partly reflect a causal effect of innovation on top income. To reach this conclusion we have to account for the possible endogeneity of our innovation measure. Endogeneity could occur through the feedback of inequality to innovation. For example, a growth in top incomes may allow incumbents to erect barriers against new entrants thereby reducing innovation and inducing a downward bias on the OLS estimate of the innovation coefficient. We develop this point further below.

Our first instrument for innovation exploits changes in the state composition of the Appropriation Committee of the Senate which allocates federal funds in particular to research across US states. As a robustness test, we will show in Section **6** that this Appropriation Committee instrument can be combined with a second instrument which exploits knowledge spillovers across states.

[30]Because the data of Lai *et al.* (2014) stop in 2010, we limit the sample period for the panel regressions to 1980-2004.

5.1 Instrumentation using the state composition of appropriation committees

We instrument for innovation using information on the time-varying state composition of appropriation committees following Aghion *et al.* (2009). To construct this instrument, we gather data on the membership of these committees over the period 1969-2010 (corresponding to Congress numbers 91 to 111).[31] The appropriation committees of the Senate and of the House of Representatives are in charge of allocating a discretionary part of the federal budget to specific federal departments or agencies. The recipient agency can then disburse these funds to specific projects based on merit and following its own regulations (see Payne, 2003 for a more detailed explanation). However, the appropriation committees can also choose to allocate funds to specific projects regardless of their quality (a congressman is usually unable to determine the potentiality of a scientific project), thus bypassing the competitive peer-review process that has been adopted in most agencies. A member of Congress who sits on an Appropriation Committee often pushes for earmarked grants in the state in which she has been elected, in order to increase her chances of reelection in that state. Although not explicitly dedicated to research and research education, those items end up being most often privileged in practice. Aghion *et al.* (2009) note that "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". Moreover, in Table 8 of their paper, they show that among all categories of non-education federal expenditures, only expenditures on highways show a positive correlation with education federal expenditures.

Further evidence to the effect that research and research-type education are the main recipient of Appropriation Committees' earmarks, can be found from looking at data from the OpenSecrets project website, which lists the main recipients of the 111$^{\text{th}}$ Congress Earmarks in the US (between 2009 and 2011). There we see that universities rank at the top together with defense companies. We shall control for state-level highway and military expenditures in our IV regressions as detailed below.

In short, a state with one of its congressmen seating on the committee is likely to receive more federal funding which will partly go to research and research education; this in turn should subsequently increase its innovation in the following years. Academic earmarks can be quite large: for example Savage (1999) mentions the case of Senator Robert F. Byrd. As

[31] Data have been collected and compared from various documents published by the House of Representatives and the Senate. The name of each congressman has been compared with official biographical information to determine the appointment date and the termination date of the congressman.

a result of this senator becoming chairman of the Senate appropriation committees in 1986, universities and college from West Virginia received 190 million dollars between 1986 and 1996.

As explained by Aghion *et al.* (2009), changes in the state composition of the Appropriation Committee have little to do with growth or innovation performance in those states. Instead, these are determined by events such as anticipated elections or more unexpectedly the death or retirement of current heads or other members of these committees, followed by a complicated political process to find suitable candidates. This process in turn gives large weight to seniority considerations with also a concern for maintaining a fair political and geographical distribution of seats. Thus reverse causality from the presence of rich individuals to the arrival of a congressman in the appropriation committee seems unlikely and it reasonable to interpret the latter event as an exogenous shock to innovation (a decrease in θ_E and θ_I in the context of our model).[32]

A related concern is that the composition of the appropriation committee would reflect the disproportionate attractiveness (for innovation and rich individuals) of states such as California and Massachusetts. However, other states have been well represented on the committee -for example Alabama had one senator, Richard C. Shelby, sitting on the Committee between 1995 and 2008-, whereas California had no committee members until the early 1990s.[33] Also, the OpenSecrets website shows the cross-state allocation of earmarks from the 111$^{\text{th}}$ Congress: the states that received the highest amount of earmarks per inhabitant, are Hawaii (not too surprising, since the Chairman of the Senate Appropriation Committee at the time, Daniel K. Inouye was himself a senator from Hawaii) and North Dakota. Other evidence reported by Savage (1999) shows that the top 5 states in terms of academic earmarks in level (not per capita) are Pennsylvania, Oregon, Florida, Massachusetts and Louisiana for fiscal years 1980-1996. The total ranking by earmarks is uncorrelated with the federal research rank and California receive almost the same amount as Hawaii.

Finally, one may be concerned by the possibility that the (rich) owner of a construction or military company would capture part of the earmarked funds. In that case, the number of congressmen seating in the committee of appropriation would be correlated with the top 1% income share, but for reasons having little to do with innovation. To deal with such possibility, we use data on total federal allocation to states by identifying the sources of state revenues. Such data can be found at the Census Bureau on a yearly basis. Using this source,

[32] This is in line with the work of political scientists (Feller, 2001; Payne, 2003) which speaks to the exogeneity in the composition of the appropriations committees and the connections between the committees and grants to research universities.

[33] More statistics on the state composition of the Senate Appropriation Committee are provided in Table 9.

we identify for each state, military expenditures and a particular type of infrastructure spending, namely highways, for which we have consistent data from 1975 onward. We control for both in our regressions.

Based on these Appropriation Committee data, different instruments for innovation can be constructed. We follow the simplest approach which is to take the number of senators (0, 1 or 2[34]) or representatives who seat on the committee for each state and at each date.

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 innovation. We choose to instrument innovation by lagged committee composition with a lag of two or three years.[35]

Table 10 shows the results from the IV regression of top income inequality on innovation, using the state composition of the Senate appropriation committee as the instrumental variable for innovation.[36,37] Column 1 uses the number of patents as a measure of innovation, column 2 uses the number of citations in a 5 year window, column 3 uses the number of claims, column 4 uses the generality weighted patent count and columns 5 and 6 use the number of patents among the top 5% and top 1% most cited patents in the year. In all cases, the instrument is lagged by 3 years with respect to the innovation variable it is instrumenting (and recall that innovation is itself lagged by 2 years in the main regression). In all cases, the resulting coefficient on innovation is positive and significant. Moreover, with the exception of columns 4 and 6, the F-statistic is above 10 suggesting that our instrument is reasonably strong.

5.2 Magnitude

We now consider the magnitude of the impact of innovation on top income inequality implied by Table 10. we see that an increase of 1% in the number of patents per capita increases the top 1% income share by 0.24% (see column 1 in Table 10) and that the effects of a 1% increase in the citation-based measures are of comparable magnitude. This means for

[34]Any given state cannot have more than two representatives on the Senate committee.

[35]Yet, one may wonder how changes in the Appropriation Committee of the Senate could affect top income inequality in the states already after four or five years. First, as pointed out by Aghion *et al.* (2009), research education funding in a state is immediately affected when representation of that state in the Appropriation Committee changes. Second, research grants often reward research projects that are already completed. Third, changes in research grants induce quick multiplier effects in the private sector (this is in line with Toole, 2007, who shows that in the pharmaceutical industry, the positive impact of public R&D on private R&D is the strongest after 1 year).

[36]The results from the first stage regression and the reduced form regression, are shown in Table B5 in Appendix B.

[37]As we have a long time series for each state, we are less concerned about 'short T' bias in panel data IV. We apply instrumental variables estimator directly to time and fixed effects regression equation (15).

example that in California where the flow of patents per capita has been multiplied by 3.1 and the top 1% income share has been multiplied by 2.4 from 1980 to 2005, the increase in innovation can explain 30% of the increase in the top 1% income share over that period. On average across US states, the increase in innovation as measured by the number of patents per capita explains about 22% of the total increase in the top 1% income share over the period between 1980 and 2005.

Yet, one should remain cautious when using our regressions to assess the true magnitude of the impact of innovation on top income inequality. Our coefficient may underestimate the true impact for at least three reasons: (i) the number of citations has increased by more than the number of patents over the past period, which suggests that the effect of innovation on top income inequality is greater than 22%; (ii) if successful, an innovator from a relatively poor state, is likely to move to a richer state, and therefore to not contribute to the top 1% share of her own state; (iii) an innovating firm may have some of its owners and top employees located in a state different from that of inventors, in which case the effect of innovation on top income inequality will not be fully internalized by the state where the patent is registered. On the other hand, if the share of innovations that get patented is increasing over time, the increase in innovation will be less than the measured increase in patenting. This would *not* bias our coefficient (as long as the increase in the share of patented innovations is the same across states), but it would mean that the increase in innovation could in fact explain less than 22% of the increase in the top 1% income share.[38]

Looking at cross state differences in a given year, we can compare the effect of innovation with that of other significant variables such as the importance of the financial sector. Our IV regression suggests that if a state were to move from the first quartile in terms of the number of patents per capita in 2005 to the fourth quartile, its top 1% income share would increase on average by 3.5 percentage points. Similarly, moving from the first to the fourth quartile in terms of the number of citations, increases the top 1% income share by 3.3 percentage points. By comparison, moving from the first quartile in terms of the size of the financial sector to the fourth quartile, would lead to a 4.5-percentage-point increase in the top 1% income share.

[38]Nevertheless, Kortum and Lerner (1999) argue that the sharp increase in the number of patents in the 90's reflected a genuine increase in innovation and a shift towards more applied research instead of regulatory changes that would have made patenting easier. Interestingly, our numbers seem consistent with the results of Bakija (2008): they found that 9.1% of the increase in the top 1% income share between 1979 and 2005 accrued to entrepreneurs, technical occupation and scientists, occupations which are the most directly linked to innovation. In addition, innovation increases executives pay and executives, managers, supervisors and business operations (outside the finance sector) account for 38.4% of the increase in the income share of the top 1%.

5.3 Discussion

The following concerns could be raised by this regression. First, it could be that some of our control variables are endogenous and that, conditional upon them, our instruments may be correlated with the unobservables in our model. To check that our results are robust to this possibility, we re-run our IV regressions, with state and year fixed effects but removing the control variables. And in each case we find that the regression coefficients on the various measures of innovation remain of the same order of magnitude and significance compared to the corresponding IV regressions with all the control variables, but the corresponding first stage F-statistic are lower (between 7 and 9.3).[39]

Second, the magnitude of the innovation coefficients in the IV regression is larger than in the OLS regressions. One potential reason has to do with the relationship between innovation and competition. More specifically, suppose that the relationship between competition and innovation lies on the upward part of the inverted-U relationship between these two variables (see Aghion *et al.*, 2005), and consider a shock to the level of competition faced by a leading firm, which increases its market power—such a shock could for example result from an increase in lobbying or from special access to a new enlarged market. This shock will increase the firm's rents which in turn should contribute to increasing inequality at the top. However, on this side of the inverted-U, this will also decrease innovation. Therefore, it induces an increase in top inequality that is bad for innovation. As it turns out, lobbying is indeed positively correlated with the top 1% income share and negatively correlated with the flow of patents. Relatedly, our model shows that a higher level of mark-ups for an incumbent who has failed to innovate can also lead to higher top income inequality and lower innovation; this higher mark-up level may in turn reflect slow diffusion of new technologies and/or high entry barriers. A second reason may have to do with credit constraints: reducing inequality may increase innovation when potential innovators that are not in top 1% face credit constraints which limit the scope of their innovative investments.[40]

Third, one might raise the possibility that some talented and rich inventors decide to move to states that are more innovative or to benefit from lower taxes. This would enhance the positive correlation between top income inequality and innovation although not for the

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

[40] E.g. see Benabou (1996), Aghion and Bolton (1997) and Aghion and Howitt (1998) (Chapter 9). The gap between the OLS and IV coefficients can also be explained by other mechanisms explored in the growth and inequality literature: for example, a high level of inequality could lead to higher taxes which can harm growth and innovation (Persson and Tabellini, 1994), and inequality can reduce innovation if it reduces the market for innovative goods (Foellmi and Zweimüller, 2015).

reason captured by our IV strategy.[41] However, building on Lai *et al.* (2014), we are able to identify the location of successive patents by a same inventor. This in turn allows us to delete patent observations pertaining to inventors whose previous patent was not registered in the same state. Our results still hold when we look at the effect of patents per capita on the top 1%, with a regression coefficient which is essentially the same as before.

5.4 Other IV results

In Appendix B, we show the results from replicating in IV the OLS regressions of Section 4. First, regressing broader measures of inequality on innovation, we find that innovation has a positive impact on top income shares but not on Gini coefficients (Table B6). Note that the effect of innovation on the top 10% remains positive but is no longer significant. Second, regressing top income inequality on innovation at various lags, we find that the effect of lagged innovation is strongest after 2 years; after four years or more, the effect becomes smaller and insignificant (Table B7). These latter findings confirm those in the corresponding OLS Table 6, and speak again to the fact that innovation has a temporary effect on top income inequality.

6 Robustness checks

In this section, we discuss the robustness of our regression results. Robustness concerns may be grouped into three categories. First, one may question the power of our instrumental variable estimations. To address this concern, we add a second instrument based on knowledge spillover and show that the overidentification test does not reject the validity of the two instruments being used jointly (see subsection 6.1). Second, potential omitted variables may bias our results. To address this concern, we add more controls in the regression of top income inequality on innovation: namely, the level of financial dependence (subsection 6.2), and a measure of agglomeration (subsection 6.4); and we show that adding all these controls does not alter our results. Finally, it could be that our results are driven by one particular economic sector or technology. We address this latter concern by successively excluding corresponding sectors or patents (subsections 6.2 and 6.3).

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

6.1 Adding a second instrument

To add power to our instrumental variable estimation, here we combine it with a second instrument which exploits knowledge spillovers across states. The idea is to instrument innovation in a state by its predicted value based on past innovation intensities in other states and on the propensity to cite patents from these other states at different time lag. Citations reflect past knowledge spillovers (Caballero and Jaffe, 1993), hence a citation network reflects channels whereby future knowledge spillovers occur. Knowledge spillovers in turn lower the costs of innovation (in the model this corresponds to a decrease in θ_I or θ_E). To build this predicted measure of innovation, we rely on the work of Acemoglu *et al.* (2016) and integrate the idea that the spillover network can be very different when looking at different lags between citing and cited patent. We thus compute a matrix of weights $w_{i,j,k}$ where for each pair of states (i, j) and for each lag k between citing and cited patents where k lies between 3 and 10 years,[42] $w_{i,j,k}$ denotes the relative weight of state j in the citations with lag k of patents issued in state i, aggregated over the period from 1975 to 1978.[43]

Using this matrix, we compute our instrument as follows: if $m(i, j, t, k)$ is the number of citations from a patent in state i, with an application date t to a patent of state j filed k years before t, and if $innov(j, t-k)$ denotes our measure of innovation in state j at time $t-k$, then we posit:

$$w_{i,j,k} = \frac{\sum_{t=1975}^{1978} m(i,j,t,k)}{\sum_{t=1975}^{1978} \sum_{l \neq i} m(i,l,t,k)} \text{ ; } KS_{i,t} = \frac{1}{Pop_{-i,t}} \sum_{k=3}^{10} \sum_{j \neq i} w_{i,j,k} innov(j, t-k),$$

where $Pop_{-i,t}$ is the population of states other than state i and the log of KS is the instrument. To reduce the risk of simultaneity, we set a one year time lag between the endogenous variable and this instrument. Without normalizing by $Pop_{-i,t}$, our measure of spillovers would mechanically put at a relative disadvantage a state which is growing relatively faster than other states.

Reverse causality from top income inequality to this knowledge spillover IV seems unlikely (the top 1% income share in one state is unlikely to cause innovations in other states).[44]

[42]Looking at all the patents in our sample granted over the period from 1975 to 2014, we find that 67% of backward citations are made to patents filed less than 10 years before the citing patent.

[43]We observe all the patents which received citations from patents granted after 1975 even if the cited patents were granted before 1975.

[44]Yet, reverse causality might arise from the same firm citing itself across different states. We check that this has, if anything, a very marginal effect by removing citations from a firm to itself in two different states

Yet, one may worry that this instrument might capture regional or industry trends that are not directly the result of innovation and yet affect both top income inequality and innovation in that state. For example, if we consider two states that are geographically close, then a boom in the first state could lead to more innovation in that state but also to more demand and more innovation in the neighboring state. In that case, if each of these two states cites the patents from the other state a lot, our spillover variable would capture a positive correlation between innovation in the two states, even though this correlation would mainly capture a common demand shock. To control for such demand shocks, we build a control variable by computing a weighted average of other states' per capita GDP using an average of the weights calculated before for k between 3 and 10.

Similarly, consider now two states that are highly involved in, say, the computer sector. Then a demand shock in this sector would boost innovation and the top 1% income share in both states, violating our exclusion restriction. To deal with such possibility, we build new weights based on the angular distance between the industry compositions of the manufacturing sectors of the two states. These new weights are averaged over a three-year window. Using these industry-composition-based weights, we compute a weighted sum of innovation in other states and divide this sum by $Pop_{-i,t}$.[45]

A first important finding is that an overidentification test that uses the spillover and appropriation committee instruments, does not reject the validity of the instruments: indeed, the p-value associated with the null hypothesis is always larger than 10% (note however that when Claims and Generality measures are used, this p-value lies slightly below 10%). This in turn reinforces the first instrument.[46]

Next, Table 11 presents the results from the IV regressions of top income inequality on the two instruments combined.[47,48] As in Table 10, the coefficients are always positive and significant (now at the 1% level). This is all the more remarkable that the two instruments are uncorrelated once one controls for states and time fixed effects. The F-statistic for the two instruments combined, are always above 10.

when constructing the weights: the results are essentially unaffected by this change.

[45]Finally, by looking at past innovation that occurred at least 3 year earlier, we set a sufficiently long time lag to reduce the risk of capturing demand shocks that are much faster.

[46]This also deals with the potential objection that innovation in other states $j \neq i$ could have a direct impact on productivity in state i, and thereby directly affect top incomes in that state. If that were the case, the two instruments combined would be correlated with the error term and therefore in that case the overidentification test would reject the null hypothesis.

[47]In the Appendix, Table B8, we show the results from the IV regressions using only the second instrument.

[48]The results from the corresponding first stage and reduced form regressions, are shown in Table B5 in the Appendix B.

6.2 The role of finance and natural resources

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

The financial sector is heavily represented in top 1% income share: Bakija (2008) find that 13.2% of primary tax payers belonging to the top 1% worked in financial sector in 2005 and 22.6% of the increase in the top income share between 1979 and 2005 accrued to individuals in the financial sector. To make sure that our effects are not mainly driven by the financial sector, in the above regressions we already controlled for the share of the financial sector in state GDP. Here, we perform additional tests. First, we add the average employee compensation in 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 (see column 1 of Table 12). 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 Massachusetts (see column 2 of Table 12). Third, financial innovations themselves might directly increase rents and therefore the top 1% income share. To account for this latter channel, we subtract patents belonging to the class 705: "Financial, Business Practice" related to financial activities in order to exclude innovations in the financial sector (see column 3 of Table 12). The regressions of the top 1% income share on innovation corresponding to these three robustness tests uses the number of citations per capita within a 5-year window to measure of innovation. In each case, the effect of innovation on the top 1% income share is significant and positive, showing very stable values when moving from one specification to another. Another potential issue related to finance is that financial development should impact both innovation (by providing easier access to credit to potential innovators) and income inequality at the top (by boosting high wages). Here we construct a variable specifically designed to directly capture this channel. For each US state, we divide the number of patent applications in that state into 16 NAICS categories mapped with patent technological classes from the USPTO[49] and we use the external financial dependence numbers computed by Kneer (2013) and averaged over the period 1980-1989. External financial dependence is defined as the ratio of capital expenditure minus cash flow divided by capital expenditure (see Rajan and Zingales, 1998). We multiply the number of patents in each NAICS sector in that state by that index and then divide by the total number of patents to compute a variable representing the level of financial dependence of innovation for each state. This

[49]The latest version of this mapping can be found in the USPTO website.

variable (denoted EFD in Table 12) should capture a variation in innovation at state-level driven by a sector that is highly dependent on external finance. Results for regressing the top 1% income share on the number of citations per capita within a 5 year window when controlling for EFD are presented in column 4. We see that the effect of innovation remains significant and the coefficient is slightly lower than the corresponding coefficient when we do not control for EFD. In addition, the effect of the financial dependence of innovations on the top 1% income share is positive and significant.

Natural resources and particularly oil extraction represent a large share of GDP in certain states (In Wyoming, West Virginia and particularly Alaska, oil extraction activities account for almost 30% of total GDP in 2010), so that in these states the top 1% income share is likely to be affected by these sectors which are quite volatile (oil extraction is highly sensitive to energy prices fluctuation). To deal with this concern, we control for the share of natural resources in GDP. In addition, we first add the share of oil extraction related activities in state GDP as a control variable; and second, we remove patents from class 208 (Mineral oils: process and production) and 196 (Mineral oils: Apparatus). Results are presented in columns 5 and 6 of Table 12. Here again, our results remain significant.

Finally Table B9 shows similar results from performing the same robustness tests in IV regressions with the appropriation committee instrument (as with the other robustness checks below, the results are similar when we use the other instrument or both).[50]

6.3 Looking at industry composition

We now check that our results are robust to controlling for the sectoral composition of innovation. First, we use the mapping between patent technological classes and NAICS sectors to remove patents related to category 334: "Computer and Electronic Products", to deal with the concern that the effect of innovation on top income inequality might be concentrated in the fast-growing computer industries. Similarly, we remove patents from the pharmaceutical sector (NAICS 3254) and from the electrical equipment sector (NAICS 335). In each case, we conduct our preferred regression using the number of citations within a

[50]Taxation is also 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, 2014 or Rotschild and Scheuer, 2016). On the other hand, a state with a large share of top income earners may have a higher incentive to raise the top marginal tax rate. The NBER TAXSIM project 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. They also provides information on the maximum tax rate for households with earnings above $1.5m. Using any of these variable as an additional control in our main regression does not affect the positive coefficient on innovation.

five-year window to measure innovation. The coefficient on innovation remains quite stable across all these specifications. Next, in our regressions we add controls for the share of these three sectors.[51] Innovation remains positively and significantly correlated with the top 1% income share in all our regressions.

Then, we use the COMTRADE database to look at the extent to which our effect of innovation on top income inequality is driven more by more export-intensive sectors. Over the period from 1975 to 2013, we identified three sectors that are particularly export-intensive: Transportation, Machinery and Electrical Machinery. When we regress the top 1% income share on the number of citations within a five-year window without counting citations to patents in these sectors, we find a positive and significant coefficient. All these results are shown in the Appendix B, Table B10 in OLS and Table B11 in IV.[52]

6.4 Controlling for agglomeration effects

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

Looking at Figure 2 in the introduction hints at the fact that this should not be such a big concern: in particular we see that neither California nor Massachusetts are among the states that show the fastest increase in both, innovation and top income inequality, over the period we analyze.

To address the agglomeration objection head on, we proceed as follows: in any state i at any date t, we look at the most, the two most and the three currently most innovative technological classes from our patent dataset in that state. We then compute the number of patents in these technology classes in that state in that year. The log of that number is our new control variable $Agglo_{it}$ which is meant to capture potential agglomeration effects

[51] In order to obtain complete series, we replace the pharmaceutical sector by the whole chemistry manufacturing sector (NAICS 325).

[52] On the link between trade, innovation and inequality, let us mention Bonfiglioli *et al.* (2016) who find that export opportunities increase innovation at the industry level and that in turn a higher level of innovation is associated with more dispersion in firm size and wage. In the same vein, Cozzi and Impullitti (2016) show that foreign competition stimulates innovation thereby inducing wage polarization. See also Dinopoulos and Segerstrom (1999) and Thoenig and Verdier (2003) for further analyses on the link between globalization, innovation and inequalities.

in state i in year t.

Running our previous regressions with these additional control variables turns out not to affect our results as seen in Table B12 in the Appendix B (see the first three columns of tables for OLS and the three other columns for IV regression results).

7 Innovation and social mobility

In this section we consider the relationship between innovation and social mobility

7.1 From cross-state to CZ-level analysis

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

To associate a patent to a CZ location, we rely on Lai *et al.* (2014) to complete the USPTO database with assignee and inventor names and location. This enables us to associate each inventor with her address and her zipcode which can be linked up to a county, and ultimately to a commuting zone. Finally, we aggregate county level data on GDP and population from the Bureau of Economics Analysis (BEA) to compute GDP per capita and population growth. All other data are taken from Chetty *et al.* (2014).

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 13 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. These controls have been selected to match our cross-state analysis as closely as possible. In addition, we add the share of the manufacturing sector, the labor force participation rate taken in 1996-2000, college graduation rate and the local expenditures in public school per student during the same period. Standard errors are clustered by state to account for potential correlation across neighboring CZs. As seen from the first two columns of Table 13, the effect of innovation on the top 1% income share 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 innovation on inequality as measured by the Gini coefficient and on the Gini coefficient for the bottom 99% of the income distribution, the coefficients are much smaller or even negative (columns 3 to 6). All these observations are consistent with our core results at the cross state level.

7.2 The effect of innovation on social mobility

Having moved from cross-state to cross-CZ analysis allows us to look at how innovation affects social mobility, using the various measures of social mobility in Chetty *et al.* (2014) combined with our local measures of innovation and with the various controls mentioned above. There, absolute upward mobility is defined as the expected percentile or "rank" (from 0 to 100) for a child whose parents belonged to some P percentile of the income distribution. Percentiles are computed from the national income distribution. The ranks are computed over the period 2011-2012 when the child is aged around 30 whereas the percentile P of parents income is calculated over the period between 1996 and 2000 when the child was aged around 15. Once again, the intensity of innovation in each CZ is measured by the average number of patents per capita, but this time, we take the averages over the period 2006-2010

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

We thus conduct the following regression:

$$log(Mob_k) = A + \beta_1 log(innov_k) + \beta_2 X_k + \varepsilon_k,$$

where Mob_k is our measure of upward social mobility, and $innov_k$ is our measure of innovation (the number of patents per capita) for CZ k. We cluster standard errors by state.

Table 14 presents our results for this cross-section OLS regression, where we add the same set of control variables as in the previous subsection. Columns 1 and 4 look at the effect of innovation on upward mobility as measured by the child expected percentile in the income distribution at 30 when parent income belongs to the 25th percentile. The effect of innovation is positive and significant. Columns 2, 3, 5 and 6 show the effects of innovation on the probability for a child to belong to the highest quintile in income distribution at age 30 when her parent belonged to a lower quintile. The lower the quintile to which parents belonged, the more positive and significant is the correlation between innovation and upward mobility. If we continue with quintiles 3 and 4, the effect of innovation on social mobility is still significant for quintile 3 (but only when college per capita and manufacturing share are not included) and negative and not significant for quintile 4. Not surprisingly, school expenditures, colleges per capita and participation rate also play a positive role in explaining upward social mobility, while the size of the manufacturing sector is negatively correlated. Finally, column 7 shows the overall effect of innovation on upward mobility measured by the probability to reach the highest quintile when parent belonged to any lower quintile. Here again, the correlation is positive.

One concern is worth mentioning here: in some CZs, the size of the top quintile is very small, reflecting the fact that it is almost impossible to reach this quintile while staying in this CZ. This case often occurs in rural areas: for example, in Greenville, a CZ in Mississippi, only 7.5% of children in 2011-2012 (when they are 30) belong to the highest quintile in the national income distribution. To address this concern, we conduct the same regressions as above but we remove CZs where the top quintile has a size below 10% and below 15% (this exclude respectively 7 and 100 CZs). All our results remain consistent with columns 1 to 6 of the previous regressions.[53] In fact, the results are even stronger, with the coefficient of innovation being now always significant at the 5% level.

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

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

7.3 Lobbying, entrant versus incumbent innovation, and social mobility

Our empirical results so far have highlighted the positive association between innovation on the one hand and social mobility on the other hand. Now, recall that our model suggests that the effect of innovation on social mobility should operate mainly through entrant innovation, and that entry barriers should dampen that effect.

To test these predictions, we conduct the same regression as in the previous section at the cross CZ level but considering separately entrant innovation and incumbent innovation on the right hand side of the regression equation, where entrants and incumbents are defined as follows: an entrant patent (resp. an incumbent patent) is one where the assignee did not patent (resp. did patent) before 2006. Table 15 presents our results. Columns 1 to 3 regress our three measures of social mobility on the number of "entrant patents" per capita, whereas columns 4 to 6 regress the three measures of social mobility on the number of "incumbent patents". The positive and significant coefficients in the first three columns, as compared to columns 4 to 6, suggest that the positive effect of innovation on social mobility is mainly driven by new entrants. This conjecture is confirmed by the horse race regression in column 7 in which both entrant innovation and incumbent innovation are included as right-hand side variables. There, we clearly see that all the effect of innovation on social mobility is associated with entrant innovation.

We next look at how lobbying intensity interacts with the effect of innovation on social mobility using cross-MSA data. As explained above, we aggregated patent applications by zipcode and then by MSA and used mobility data from Chetty *et al.* (2014) who only provide absolute mobility data and no transition matrix for MSAs. Our regular control variables (GDP per capita, population growth, share of financial sector and government size) have been found in the BEA and averaged over the period 2006-2010. Overall, we are left with 352 MSAs which can be separated in two groups of equal size, respectively with high and low lobbying activities. Columns 1 and 2 of Table 16 show the effect of innovation as measured by the number of entrant patents per capita (in log) on the logarithm of absolute upward mobility. Column 1 focuses on MSAs above median in terms of lobbying activities and column 2 on other MSAs. Similarly, columns 3 and 4 look at the effect of the number of incumbent patents per capita on absolute upward mobility. We see that the effect of entrant innovation on social mobility is positive and significant only for MSAs that are below median in terms of lobbying intensity. In addition, incumbent innovation has no effect on social mobility, whether we look at MSAs above or below the median in terms of lobbying intensity. These results confirm the idea that lobbying dampens the impact of innovation on social mobility by reducing the effect of entrant innovation.

8 Conclusion

In this paper we have looked at the relationship between top income inequality and innovation. First, we found positive and significant correlations between measures of innovation on the one hand, and top income inequality on the other hand. We also showed that the correlations between innovation and broad measures of innovation are not significant, and that top income inequality is not correlated with highly lagged innovation. Second, we argued that these correlations at least partly reflect a causal effect from innovation to top income shares. Third, we showed that innovation is positively associated with social mobility.

In this paper, our approach has been to look at the aggregate effect of innovation on top income inequality. This is an essential first step to assess the overall quantitative importance of innovation in top income inequality. Thus our analysis complements more microeconomics studies which explore the relationship between innovation, top income inequality and social mobility using individual data on revenues and patenting.[54]

Overall, our findings suggest interesting avenues for further research on (innovation-led) growth, inequality and social mobility. A first extension would be to contrast innovation and other sources of top income inequality, for example from financial and lobbying activities, by looking at the effects of these other sources on other measures of inequality and on social mobility. Our conjecture is that, unlike innovation, lobbying should be positively correlated with broad measures of inequality, and negatively correlated with social mobility.

Relatedly, it would be interesting to link this work directly with the inverted-U results in Aghion *et al.* Aghion *et al.* (2005), looking at how competition (or the lack of it) affects top income inequality both directly and through its effects on innovation, and examining the circumstances under which increasing top inequality may induce a reduction in competition and thereby depress innovative activity.

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

Another avenue for future research would be to look at the effect of innovation on top income inequality in cross-country panel data. Preliminary OLS regressions show a positive

[54]In Aghion *et al.* (2015) such a study is conducted using Finnish individual data over the period 1990-2000. See also Toivanen and Vaananen (2012) and Bell *et al.* (2015).

and significant correlation between our innovation measures and top 1% income share in cross-country panel.

Finally, our results on the impact of lobbying suggest that the relationship between innovation and income inequality depends upon institutional factors which vary across countries. Further research should thus look deeper into how institutions affect the relationship between top income inequality and innovation.

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Tables used in the main text

Table 1: Descriptive statistics by state in two distinctive years

State	1980		2005		State	1980		2005	
	Innovation	Top 1%	Innovation	Top 1%		Innovation	Top 1%	Innovation	Top 1%
AK	66	5.33	134	12.47	**MT**	79	8.02	685	16.35
AL	90	10.01	346	18.48	**NC**	150	9.03	1 878	17.04
AR	61	10.05	231	16.68	**ND**	89	9.62	926	13.23
AZ	381	8.56	2 209	22.66	**NE**	75	9.33	639	15.24
CA	586	9.91	7 082	24.20	**NH**	443	8.48	3 941	18.01
CO	437	9.31	3 165	19.56	**NJ**	1 051	9.83	3 006	20.77
CT	861	12.24	3 395	31.02	**NM**	142	8.90	1 168	15.63
DC	199	14.48	819	23.94	**NV**	310	11.09	2 394	33.30
DE	1 271	10.19	2 311	21.38	**NY**	481	12.08	2 464	30.25
FL	234	12.23	942	31.78	**OH**	449	8.98	1 742	15.86
GA	130	8.95	1 336	19.11	**OK**	529	11.44	878	17.74
HI	58	7.52	551	16.47	**OR**	215	8.25	4 830	16.91
IA	202	8.24	990	12.92	**PA**	492	9.37	1 524	18.71
ID	156	7.68	7 320	18.08	**RI**	246	10.25	1 582	17.36
IL	521	9.63	1 747	21.67	**SC**	158	8.16	564	17.74
IN	368	8.44	1 458	15.52	**SD**	51	8.58	250	16.94
KS	142	10.17	1 328	16.09	**TN**	170	10.09	800	18.76
KY	174	9.69	487	15.76	**TX**	389	12.18	2 267	21.90
LA	139	11.22	293	17.65	**UT**	301	7.79	2 575	18.49
MA	680	10.03	6 794	23.79	**VA**	245	7.97	1 333	17.12
MD	402	8.13	1 998	17.34	**VT**	385	7.97	6 359	16.31
ME	135	8.55	598	15.66	**WA**	245	8.37	9 994	19.69
MI	562	8.91	2 331	16.12	**WI**	303	8.21	1 754	16.48
MN	545	9.31	4 899	18.24	**WV**	187	9.54	205	14.97
MO	185	9.96	896	17.11	**WY**	82	9.00	620	28.52
MS	40	10.48	182	15.81					

Notes: Number of citations within a five-year window per capita and top 1% income share for all 51 states in 1980 and 2005.

Table 2: Descriptive statistics by measures of innovation and top 1% income share in two distinctive years

1980	Mean	p25	p50	p75	Min	Max
Top 1%	9.45	8.37	9.31	10.09	5.33	14.48
Patents	141	71	113	189	27	492
Cit5	312	139	234	443	40	1271
Claims	1564	733	1192	2321	245	5959
Generality	35	17	25	47	5	138
Top5	8	2	5	11	0	40
Top1	1	0	1	2	0	4
2005	Mean	p25	p50	p75	Min	Max
Top 1%	19.07	16.12	17.65	20.77	12.47	33.30
Patents	292	127	228	407	46	898
Cit5	2122	639	1458	2464	134	9994
Claims	5491	2234	4411	763	784	20117
Generality	120	50	89	184	15	344
Top5	12	3	8	14	0	80
Top1	4	1	3	5	0	18

Notes: Summary statistics includes mean, quartiles' thresholds, minimum and maximum for our six measures of innovation and the top 1% income share (relevant variables are defined in Table 3).

Table 3: Variable description and notation

Variable names	**Description**
	Measures of inequality
Top 1%	Share of income own by the richest 1%.
Top 10%	Share of income own by the richest 10%.
Avgtop	Average income share for the percentiles 10 to 2 in the income distribution.
Gini	Gini index of inequality.
G99	Gini index restricted to the bottom 99% of income distribution.
Theil	Theil index of inequality.
Atkinson	Atkinson index of inequality.
	Measures of innovation
Patent	Number of patents granted by the USPTO per inhabitants.
Cit5	Total number of citation received no longer than 5 years after applications per inhabitant.
Claims	Total number of claims associated with patents per inhabitants.
Generality	Total number of patents weighted by the generality index per inhabitants.
Top5	Number of patents in the top 5% most cited per inhabitants.
Top1	Number of patents in the top 1% most cited per inhabitants.
	Measures of social mobility
AM25	Expected percentile of a child at 30 whose parents belonged to the 25^{th} percentile of income distribution in 2000.
AM50	Expected percentile of a child at 30 whose parents belonged to the 50^{th} percentile of income distribution in 2000.
P5-i	Probability for a child at 30 to belong to the 5^{th} quintile of income distribution if parent belonged to the i^{th} quintile, $i \in \{1, 2\}$.
P5	Probability for a child at 30 to belong to the 5^{th} quintile of income distribution if parent belonged to lower quintiles.
	Control variables
Gdppc	Real GDP per capita in US $ (in log).
Popgrowth	Growth of total population.
Sharefinance	Share of the state GDP accounted for by the financial sector. Between 0 and 1.
Unemployment	Unemployment rate. Between 0 and 1.
Gvtsize	Share of the state GDP accounted for by the government sector. Between 0 and 1.
	Additional control variables at the CZ level
Participation Rate	Labor force participation rate.
College per capita	College graduation rate.
School Expenditure	Average expenditures per student in public schools (in log).
Employment Manuf	Share of employed persons 16 and older working in manufacturing.

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

Table 4: Top 1% income share and innovation

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.019	0.030***	0.025**	0.031***	0.013***	0.008**
	(1.46)	(3.53)	(2.28)	(2.69)	(3.01)	(2.00)
Gdppc	-0.058	-0.091	-0.090	-0.089	-0.078	-0.077
	(-0.99)	(-1.52)	(-1.47)	(-1.47)	(-1.32)	(-1.30)
Popgrowth	0.148	-0.100	-0.117	-0.083	-0.139	-0.134
	(0.16)	(-0.10)	(-0.12)	(-0.08)	(-0.14)	(-0.13)
Sharefinance	0.274	0.433**	0.386**	0.397**	0.391**	0.321*
	(1.41)	(2.24)	(2.01)	(2.08)	(2.04)	(1.72)
Gvtsize	0.119	0.184	0.086	0.101	0.193	0.115
	(0.37)	(0.55)	(0.25)	(0.30)	(0.56)	(0.34)
Unemployment	-0.422	-0.645	-0.595	-0.588	-0.624	-0.563
	(-0.97)	(-1.48)	(-1.36)	(-1.36)	(-1.42)	(-1.31)
R^2	0.908	0.915	0.914	0.915	0.915	0.914
Observations	1785	1632	1632	1632	1632	1632

Notes: The table presents estimates of different measures of innovation on the top 1% income share of state income. We consider different measures of innovation which are all lagged by 2 years and standardized by state population: column (1) uses the number of patents, column (2) uses the number of citations received within a five-year window, column (3) uses the number of claims, column (4) uses the number of patents weighted by their generality index, column (5) uses the number of patents belonging to the top 5% most cited in the year and column (6) uses the number of patents belonging to the top 1% most cited in the year. All these measures as well as the dependent variable are taken in log. Time span: 1977-2011 for column (1) and 1977-2008 for columns (2) to (6). Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 5: Innovation and various measures of inequality

Dependent variable	Top 1%	Avgtop	Top 10 %	Overall Gini	G99	Atkinson
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation	0.030***	0.011***	0.019***	-0.001	-0.007*	0.015***
	(3.53)	(2.78)	(4.29)	(-0.17)	(-1.65)	(3.58)
Gdppc	-0.091	-0.054**	-0.053**	0.022	0.029	0.061**
	(-1.52)	(-2.19)	(-2.02)	(1.09)	(1.18)	(2.39)
Popgrowth	-0.100	0.378	0.415	-0.319*	-0.403*	0.374
	(-0.10)	(0.96)	(0.99)	(-1.79)	(-1.78)	(1.32)
Sharefinance	0.433**	0.250***	0.499***	0.100	-0.078	0.304**
	(2.24)	(3.28)	(4.22)	(1.45)	(-1.05)	(2.42)
Gvtsize	0.184	-0.145	-0.692***	0.333***	0.691***	-0.478***
	(0.55)	(-0.86)	(-3.60)	(2.66)	(4.27)	(-3.14)
Unemployment	-0.645	0.017	-0.222	-0.023	0.164	-0.107
	(-1.48)	(0.11)	(-1.24)	(-0.20)	(1.08)	(-0.70)
R^2	0.915	0.430	0.821	0.870	0.750	0.933
Observations	1632	1632	1632	1632	1632	1632

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on various measures of inequality: column (1) uses the top 1% income share, column (2) uses the average size of percentiles 2 to 10 in the income distribution, column (3) uses the 10% income share, column (4) uses the gini coefficient, column (5) uses the gini coefficient excluding the first percentile of the income distribution and column (6) uses the Atkinson index with a coefficient of 0.5. Innovation measures have been lagged by 2 years and are taken in log. The dependent variable is also in log in all columns. Time span: 1976-2008. Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with auto-correlation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 6: Top 1% income share and innovation at different lags

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	2 years	3 years	4 years	5 years	6 years	All lags
Innovation	0.029***	0.024**	0.016	0.007	-0.007	
	(2.87)	(2.29)	(1.59)	(0.68)	(-0.67)	
Gdppc	-0.146**	-0.144**	-0.141**	-0.136*	-0.127*	-0.140**
	(-2.07)	(-2.05)	(-1.97)	(-1.88)	(-1.79)	(-2.01)
Popgrowth	0.701	0.766	0.749	0.740	0.687	0.566
	(0.59)	(0.65)	(0.63)	(0.63)	(0.58)	(0.47)
Sharefinance	0.582***	0.550***	0.512***	0.480**	0.446**	0.616***
	(2.92)	(2.78)	(2.63)	(2.49)	(2.33)	(3.10)
Gvtsize	0.177	0.172	0.137	0.097	0.030	0.077
	(0.46)	(0.43)	(0.34)	(0.24)	(0.07)	(0.20)
Unemployment	-0.488	-0.432	-0.390	-0.334	-0.279	-0.544
	(-0.97)	(-0.87)	(-0.78)	(-0.67)	(-0.57)	(-1.07)
Lag 2						0.041**
						(2.37)
Lag 3						0.022
						(1.15)
Lag 4						0.009
						(0.45)
Lag 5						-0.008
						(-0.49)
Lag 6						-0.045***
						(-2.92)
R^2	0.877	0.877	0.877	0.876	0.876	0.879
Observations	1428	1428	1428	1428	1428	1428

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on the top 1% income share at different lags column (1) uses a two-year lag between the measure of innovation and the dependent variable, column (2) uses three-year lags etc. Column 6 uses all these lags from 2 to 6 at the same time (variables Lag2, Lag3...). Both our measure of innovation and the dependent variable are taken in log in all columns. Time span: 1981-2008. Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 7: Top 1% income share, innovation and the role of lobbying intensity

Dependent variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of innovation	Cit5	Claims	Generality	Top5	Top1
Innovation	0.142***	0.078*	0.139***	0.082***	0.044***
	(4.13)	(1.81)	(2.98)	(5.23)	(2.75)
Innovation * Lobbying	-0.217***	-0.220***	-0.250***	-0.149***	-0.096***
	(-5.50)	(-4.84)	(-5.38)	(-5.60)	(-3.24)
Lobbying	1.430***	1.822***	1.065***	0.224	0.098
	(4.89)	(4.61)	(4.38)	(1.63)	(0.63)
Gdppc	0.020	0.019	0.010	-0.010	0.006
	(0.26)	(0.23)	(0.13)	(-0.12)	(0.08)
Popgrowth	3.477	4.055*	3.874*	3.732	4.220*
	(1.56)	(1.71)	(1.64)	(1.63)	(1.73)
Sharefinance	0.562	0.506	0.488	0.486	0.556
	(1.40)	(1.27)	(1.22)	(1.20)	(1.46)
Gvtsize	2.829***	2.684***	2.803***	2.635***	2.406***
	(3.07)	(2.77)	(3.01)	(2.81)	(2.59)
Unemployment	-1.197	-0.857	-0.819	-1.290	-1.258
	(-1.33)	(-0.92)	(-0.88)	(-1.44)	(-1.30)
R^2	0.753	0.743	0.745	0.752	0.735
Observations	561	561	561	561	561

Notes: The table presents estimates of different measures of innovation on the top 1% income share of state income. We consider different measures of innovation which are all lagged by 2 years and standardized by state population: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index, column (4) uses the number of patents belonging to the top 5% most cited in the year and column (5) uses the number of patents belonging to the top 1% most cited in the year. All these measures as well as the dependent variable are taken in log. *Lobbying* is measured as the total amount of lobbying in the state divided by population as explained in section 4.4. In each case, we add an interaction terms between our measure of innovation and our measure of lobbying intensity. This dummy is not included in the regression as is would be captured by state fixed effect. Time span: 1998-2008 for all columns. Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 8: Top 1% income share and innovation by entrants and incumbents

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation		Patents			Cit5	
Innovation by Entrants	0.031**		0.031**	0.014**		0.013**
	(2.30)		(2.26)	(2.28)		(2.06)
Innovation by Incumbents		0.011	0.002		0.011	0.008
		(0.87)	(0.16)		(1.37)	(1.05)
Gdppc	-0.107	-0.130*	-0.108	-0.189***	-0.190***	-0.195***
	(-1.53)	(-1.87)	(-1.51)	(-2.74)	(-2.68)	(-2.84)
Popgrowth	0.890	0.718	0.891	-0.022	-0.188	-0.058
	(0.80)	(0.64)	(0.80)	(-0.02)	(-0.13)	(-0.04)
Sharefinance	0.429**	0.488**	0.434**	0.585**	0.721***	0.634**
	(2.24)	(2.54)	(2.19)	(2.42)	(3.01)	(2.53)
Unemployment	-0.303	-0.446	-0.311	-0.291	-0.422	-0.347
	(-0.66)	(-0.93)	(-0.66)	(-0.54)	(-0.75)	(-0.65)
Gvtsize	0.162	0.130	0.162	-0.530	-0.496	-0.486
	(0.43)	(0.34)	(0.44)	(-1.21)	(-1.09)	(-1.10)
R^2	0.880	0.878	0.881	0.828	0.827	0.829
Observations	1479	1479	1479	1224	1224	1224

Notes: The table presents estimates of two different measures of innovation lagged by two years (number of patents and number of citations within a five-year window, denoted Cit3, per inhabitants) on the top 1% income share of state income. We consider two different types of innovation, innovation by entrants as defined by assignees that first patented less than three years ago and innovation by incumbents as defined by assignees that first patented more than three years ago: columns (1) to (3) use the number of patents, columns (4) to (6) use the number of citations within a five-year window. All these measures as well as the dependent variable are taken in log. Time span: 1981-2008 for columns (1) to (3) and 1981-2004 for columns (4) to (6) due to availability of the disambiguation database on assignees and inventors from Lai *et al.* (2014). Variable description is given in Table 3.

Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with auto-correlation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 9: Descriptive statistics on the Senate appropriation committee composition.

State	Number of years with: 1 Senator	Number of years with: 2 Senators	State	Number of years with: 1 Senator	Number of years with: 2 Senators
AK	28	0	**MT**	22	0
AL	14	0	**NC**	2	0
AR	28	0	**ND**	25	10
AZ	19	0	**NE**	16	0
CA	14	0	**NH**	32	0
CO	17	0	**NJ**	26	0
CT	12	0	**NM**	36	0
DC	0	0	**NV**	31	1
DE	3	0	**NY**	13	0
FL	21	0	**OH**	6	0
GA	10	0	**OK**	15	0
HI	32	6	**OR**	24	0
IA	19	4	**PA**	35	0
ID	24	0	**RI**	11	0
IL	12	0	**SC**	33	0
IN	9	0	**SD**	17	0
KS	7	0	**TN**	19	0
KY	26	0	**TX**	19	0
LA	32	0	**UT**	27	0
MA	8	0	**VA**	0	0
MD	28	1	**VT**	29	2
ME	3	0	**WA**	21	9
MI	1	0	**WI**	30	8
MN	0	0	**WV**	38	0
MO	29	0	**WY**	7	0
MS	30	8			

Notes: The table gives the number of years between 1970 and 2008 with exactly one (resp. 2) senator seating in the appropriation committee. The exact composition can be found in the appropriation committee official website.

Table 10: Regression of innovation on top 1% income share using instrument based on Appropriation Committee composition in the Senate

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.237*	0.172**	0.210**	0.292*	0.129*	0.148*
	(1.85)	(2.03)	(1.97)	(1.81)	(1.93)	(1.81)
Gdppc	-0.200*	-0.212**	-0.251**	-0.253**	-0.150*	-0.207*
	(-1.88)	(-2.21)	(-2.22)	(-2.10)	(-1.81)	(-1.95)
Popgrowth	0.377	-0.011	0.073	0.364	-0.031	0.104
	(0.36)	(-0.01)	(0.07)	(0.32)	(-0.03)	(0.08)
Sharefinance	0.726**	0.936**	0.894**	1.082**	0.998**	0.719*
	(1.98)	(2.28)	(2.21)	(2.09)	(2.12)	(1.82)
Gvtsize	-0.166	0.114	-0.218	-0.071	0.873	0.771
	(-0.44)	(0.24)	(-0.53)	(-0.14)	(1.11)	(0.94)
Unemployment	-1.131	-1.229*	-1.224*	-1.227*	-1.505*	-1.323
	(-1.57)	(-1.79)	(-1.79)	(-1.71)	(-1.79)	(-1.63)
Highways	0.027**	0.030**	0.029**	0.030**	0.031**	0.031**
	(2.18)	(2.35)	(2.24)	(2.07)	(2.28)	(2.08)
Military	0.008	0.011*	0.009*	0.011*	0.008	0.008
	(1.59)	(1.85)	(1.72)	(1.85)	(1.54)	(1.27)
R^2	0.887	0.897	0.897	0.874	0.874	0.834
1^{st} stage F-stat	13.84	14.64	14.43	7.91	10.33	7.28
Observations	1750	1600	1600	1600	1600	1600

Notes: The table presents estimates of different measures of innovation lagged by two years on the top 1% income share of state income: column (1) uses the number of patents, column (2) uses the number of citations received within a five-year window, column (3) uses the number of claims, column (4) uses the number of patents weighted by their generality index, column (5) uses the number of patents belonging to the top 5% most cited in the year and column (6) uses the number of patents belonging to the top 1% most cited in the year. All these measures as well as the dependent variable are taken in log. DC is removed from the sample because it has no senator. Time span: 1977-2011 for column (1) and 1977-2008 for columns (2) to (6). Variable description is given in Table 3.
Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that seat on the appropriation committee. The lag between the instrument and the endogeneous variable is set to 3 years. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 11: Robustness 1: regression of innovation on top 1% income share using two instruments

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.219***	0.132***	0.160***	0.174***	0.108***	0.180***
	(3.47)	(3.65)	(3.51)	(3.49)	(3.52)	(3.12)
lgdppc	-0.208**	-0.165*	-0.179*	-0.150	-0.104	-0.194*
	(-2.12)	(-1.74)	(-1.82)	(-1.56)	(-1.12)	(-1.68)
Highways	0.028***	0.030***	0.028***	0.027**	0.033***	0.041***
	(2.69)	(2.89)	(2.60)	(2.47)	(3.08)	(2.99)
Military	0.007	0.009	0.007	0.006	0.006	0.015*
	(1.25)	(1.50)	(1.25)	(1.08)	(1.05)	(1.80)
Popgrowth	1.796	1.453	1.484	1.447	1.426	1.676
	(1.48)	(1.23)	(1.31)	(1.24)	(1.13)	(1.18)
Sharefinance	0.971***	1.246***	1.157***	1.187***	1.450***	1.593***
	(3.75)	(4.85)	(4.60)	(4.71)	(4.63)	(3.83)
Gvtsize	0.040	0.134	-0.018	0.025	0.892	1.714*
	(0.08)	(0.26)	(-0.04)	(0.05)	(1.36)	(1.80)
Unemployment	-1.153*	-0.992*	-0.931	-0.900	-1.323*	-1.615*
	(-1.82)	(-1.67)	(-1.62)	(-1.57)	(-1.92)	(-1.84)
Spatial Corr	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.797	0.834	0.834	0.832	0.804	0.638
1^{st} stage F-stat	39.56	53.98	51.49	46.94	35.46	11.93
Sargan-Hansen J-stat (p-value)	0.130	0.193	0.0844	0.086	0.418	0.818
Observations	1450	1300	1300	1300	1300	1300

Notes: The table presents estimates of different measures of innovation lagged by two years on the top 1% income share of state income: column (1) uses the number of patents, column (2) uses the number of citations received within a five-year window, column (3) uses the number of claims, column (4) uses the number of patents weighted by their generality index, column (5) uses the number of patents belonging to the top 5% most cited in the year and column (6) uses the number of patents belonging to the top 1% most cited in the year. All these measures as well as the dependent variable are taken in log. DC is removed from the sample because it has no senator. Time span: 1983-2011 for columns (1) 1983-2008 for columns (2) to (6). Variable description is given in Table 3.

Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that seat on the appropriation committee and by a measure of spillover as described in section6.1. The lag between the first instrument and the endogeneous variable is set to 3 years while the lag between the second instrument and the endogeneous variable is 1 year. Control for spatial correlation involves adding two additional controls for demand shocks as explained in subsection 6.1. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 12: Robustness 2: financial sector and natural resources

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation	0.030***	0.032***	0.030***	0.020**	0.028***	0.030***
	(3.42)	(3.64)	(3.56)	(2.14)	(3.30)	(3.49)
Gdppc	-0.085	-0.078	-0.091	-0.092	-0.061	-0.091
	(-1.39)	(-1.24)	(-1.52)	(-1.50)	(-1.07)	(-1.52)
Popgrowth	-0.061	-0.148	-0.101	-0.122	-0.152	-0.104
	(-0.06)	(-0.14)	(-0.10)	(-0.12)	(-0.15)	(-0.10)
Sharefinance	0.485**	0.836***	0.430**	0.415**	0.364*	0.432**
	(2.49)	(3.76)	(2.24)	(2.19)	(1.93)	(2.24)
Gvtsize	0.137	0.291	0.165	0.228	0.249	0.175
	(0.42)	(0.85)	(0.49)	(0.68)	(0.71)	(0.53)
Unemployment	-0.582	-1.111**	-0.639	-0.720*	-0.706	-0.644
	(-1.30)	(-2.51)	(-1.47)	(-1.65)	(-1.64)	(-1.48)
RemunFinance	-0.001					
	(-1.08)					
EFD				0.385***		
				(2.81)		
Oil					-0.003	
					(-0.63)	
Mining					1.208*	
					(1.78)	
R^2	0.915	0.919	0.915	0.916	0.916	0.915
Observations	1632	1504	1632	1632	1632	1632

Notes: The table presents estimates of the number of citations received with a five-year window per inhabitants lagged by two years on the top 1% income share of state income: in column (1) we control for average compensation in the financial sector, in column (2), NY, CT, DE and MA (the state with the largest financial sectors) are dropped from the dataset, in column (3), finance-related patents have been removed, in column (4) we control for financial dependence in the state as explained in section 6.2, in column (5) we control for the size of oil and mining sectors and in column (6) oil-related patents have been removed in the count of citations. Time Span: 1977-2008. Variables *Oil* and *NaturalRessource* measure the share of oil related and natural resources extraction activities in GDP, variable *RemunFinance* measures the compensation per employee in the financial sector and variable *EFD* measures the financial dependence of innovation. Other variables description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. Innovation as well as the top 1% income share are taken in log. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 13: Innovation and inequality at the Commuting Zone level

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

Notes: The table presents estimates of the number of patents per inhabitants on various measures of inequality at the Commuting Zone (CZ) level: columns (1) and (2) use the top 1% income share of CZ income, columns (3) and (4) use the Gini index and columns (5) and (6) use the Gini index for the bottom 99% of the income distribution. Columns (2), (4) and (6) add additional controls. All innovation and inequalities measures are averaged over the period 1996-2000 and taken in logs. A dummy equal to one if the CZ belongs to an urban area is included but not reported. Variable description is given in Table 3.
Cross section OLS regressions. t/z statistics in parentheses, computed with heteroskedasticity robust standard errors clustered at the state level. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 14: Innovation and social mobility at the Commuting Zone level

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

Notes: The table presents estimates of the number of patents per inhabitants on various measures of social mobility at the Commuting Zone (CZ) level: columns (1) and (4) use the expected percentile of the income distribution when your parent belongs to the 25^{th} percentile, columns (2) and (5) use the transition probability between the first and the fifth quantiles in the income distribution, columns (3) and (6) use the transition probability between the second and the fifth quantiles in the income distribution, and column (7) uses the probability of reaching the highest quantile in the income distribution when parents did not belong to this quantile. The number of patents per inhabitants is averaged over the period 2006-2010 and social mobility measures are taken when the child is 30 between 2011 and 2012 compared to his parents during the period 1996-2000, all these measures are taken in logs. A dummy equal to one if the CZ belongs to an urban area is included but not reported. Variable description is given in Table 3.
Cross section OLS regressions. t/z statistics in parentheses, computed with heteroskedasticity robust standard errors clustered at the state level. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 15: Innovation and social mobility at the Commuting Zone level. Entrants and incumbents innovation

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

Notes: The table presents estimates of the number of patents per inhabitants on various measures of social mobility at the Commuting Zone (CZ) level. We consider different measures of social mobility: columns (1), (4) and (7) use the expected percentile of the income distribution when your parent belongs to the 25^{th} percentile, columns (2) and (5) use the transition probability between the first and the fifth quantiles in the income distribution, columns (3) and (6) use the transition probability between the second and the fifth quantiles in the income distribution, Innovation has been considered separately whether patents come from entrants (firms that first patented during the period 2006-2010 and incumbents (firms that first patented before 2006). The number of patents per inhabitants is averaged over the period 2006-2010 and social mobility measures are taken when the child is 30 between 2011 and 2012 compared to his parents during the period 1996-2000, all these measures are taken in logs. A dummy equal to one if the CZ belongs to an urban area is included but not reported. Variable description is given in Table 3.
Cross section OLS regressions. t/z statistics in parentheses, computed with heteroskedasticity robust standard errors clustered at the state level. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 16: Innovation and social mobility at the MSA level. Entrants and incumbents innovation and the role of lobbying

Dependent variable	AM25			
	(1)	**(2)**	**(3)**	**(4)**
Innovation by Entrants	0.012	0.028***		
	(1.28)	(2.72)		
Innovation by Incumbents			0.005	0.014
			(0.73)	(1.46)
Gdppc	0.044	0.030	0.046	0.028
	(1.66)	(0.94)	(1.68)	(0.81)
Popgrowth	0.002	0.000	0.003	0.000
	(1.47)	(0.16)	(1.64)	(0.16)
Sharefinance	0.000	-0.003***	0.000	-0.003**
	(0.15)	(-2.82)	(0.40)	(-2.19)
Gvtsize	-0.001	0.001	-0.001	0.001
	(-0.41)	(0.78)	(-0.47)	(0.86)
R^2	0.107	0.079	0.100	0.049
Observations	176	176	176	176

Notes: The table presents estimates of the number of patents per inhabitants on various measures of social mobility at the Metropolitan Statistical Areas (MSA) level: columns (1) and (3) focus on MSA that are below the median in terms of lobbying intensity during the period 2006-2010 and columns (2) and (4) focus on other MSA. The measure of mobility is the expected percentile of the income distribution when your parent belongs to the 25^{th} percentile. Innovation has been considered separately whether patents come from entrants (firms that first patented during the period 2006-2010 and incumbents (firms that first patented before 2006). The number of patents per inhabitants is averaged over the period 2006-2010 and social mobility measures are taken when the child is 30 between 2011 and 2012 compared to his parents during the period 1996-2000, all these measures are taken in logs. Variable description is given in Table 3.
Cross section OLS regressions. t/z statistics in parentheses, computed with heteroskedasticity robust standard errors clustered at the state level. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

A Online Appendix A

A.1 Proofs for subsections 2.2.2 and 2.2.3

Proof of Proposition 2

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

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

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

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

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

Proof of Proposition 3

Using (5), we rewrite:

$$\frac{w_t}{Y_t} = \frac{1}{L}\left(1-\pi_L-(\pi_H-\pi_L)\left(x_I^*+(1-z)\,x_E^*\right)\right)$$

We then obtain

$$\frac{\partial\,(w_t/Y_t)}{\partial x_I^*} = -\frac{1}{L}(\pi_H-\pi_L) \text{ and } \frac{\partial\,(w_t/Y_t)}{\partial x_E^*} = -\frac{1-z}{L}(\pi_H-\pi_L)\,.$$

Using (14), we get:

$$\frac{\partial rel\_net\_share}{\partial x_I^*} = \left(\frac{1}{2}(\pi_H-\pi_L)\frac{w_t}{Y_t}+\frac{\pi_H-\pi_L}{L}\left(\begin{array}{c}\pi_L+\frac{1}{2}(\pi_H-\pi_L)\,x_I^*\\ +\left(\frac{1}{2}\pi_H-\pi_L\right)(1-z)\,x_E^*\end{array}\right)\right)\left(\frac{Y_t}{w_t}\right)^2\frac{1}{L_t}$$

$$\frac{\partial rel\_net\_share}{\partial x_E^*} = \left(\begin{array}{c} \left(\frac{1}{2}\pi_H + \frac{1}{2}\frac{w_t}{Y_t} - \pi_L\right)(1-z)\frac{w_t}{Y_t} + \\ \frac{(1-z)(\pi_H - \pi_L)}{L} \left(\begin{array}{c} \pi_L + \frac{1}{2}(\pi_H - \pi_L)x_I^* \\ + \left(\frac{1}{2}\pi_H - \pi_L\right)(1-z)x_E^* \end{array} \right) \end{array} \right) \left(\frac{Y_t}{w_t}\right)^2 \frac{1}{L_t}$$

Note that

$$\begin{aligned} A &= \pi_L + \frac{1}{2}(\pi_H - \pi_L)x_I^* + \left(\frac{1}{2}\pi_H - \pi_L\right)(1-z)x_E^* \\ &= \pi_L\left(1 - \frac{1}{2}(1-z)x_E^*\right) + \frac{1}{2}(\pi_H - \pi_L)(x_I^* + (1-z)x_E^*) \end{aligned}$$

is positive since $(1-z)x_E^* < 1$. Therefore $\frac{\partial rel\_net\_share}{\partial x_I^*} > 0$ and $\frac{\partial rel\_net\_share}{\partial x_E^*} > 0$ if $\frac{1}{2}\pi_H + \frac{1}{2}\frac{w_t}{Y_t} - \pi_L > 0$.

We know that an increase in θ_E has no impact on x_I^* but decreases x_E^*, therefore we get that it reduces the relative net shares whenever $\frac{1}{2}\pi_H + \frac{1}{2}\frac{w_t}{Y_t} - \pi_L > 0$. An increase in θ_I on the other hand affects both x_I^* but also x_E^*, as we have:

$$\frac{\partial x_E^*}{\partial \theta_I} = \frac{\frac{1}{L}(\pi_H - \pi_L)}{\theta_E - \frac{1}{L}(1-z)^2(\pi_H - \pi_L)}\frac{\partial x_I^*}{\partial \theta_I},$$

We can then write

$$\begin{aligned} & \frac{\partial rel\_net\_share}{\partial \theta_I^*} \\ = \; & \frac{\partial rel\_net\_share}{\partial x_I^*}\frac{\partial x_I}{\partial \theta_I} + \frac{\partial rel\_net\_share}{\partial x_E^*}\frac{\partial x_E}{\partial \theta_E} \\ = \; & \left(\begin{array}{c} (\pi_H - \pi_L)\frac{w_t}{Y_t}\frac{1}{2}\frac{\theta_E - \frac{1}{L}(1-z)^2\left(\pi_L - \frac{w_t}{Y_t}\right)}{\theta_E - \frac{1}{L}(1-z)^2(\pi_H - \pi_L)} \\ + \frac{(\pi_H - \pi_L)}{L}A\left(1 + \frac{\frac{1}{L}(1-z)^2(\pi_H - \pi_L)}{\theta_E - \frac{1}{L}(1-z)^2(\pi_H - \pi_L)}\right) \end{array} \right) \left(\frac{Y_t}{w_t}\right)^2 \frac{1}{L_t}\frac{\partial x_I^*}{\partial \theta_I} \end{aligned}$$

Note that $x_E^* < 1$, requires $(\pi_H - w)(1-z) < \theta_E$. Moreover as $L > 1$, we must have

$$\theta_E - \frac{1}{L}(1-z)^2\left(\pi_L - \frac{w_t}{Y_t}\right) > \frac{1}{L}(1-z)^2(\pi_H - \pi_L).$$

Hence the relative net share is always decreasing in θ_I.

Finally consider the case where L is large such that $\frac{w_t}{Y_t}$ is small, then we have

$$\frac{w_t}{Y_t} \approx \frac{1}{L}\left(1-\pi_L-(\pi_H-\pi_L)\left(\frac{\pi_H-\pi_L}{\theta_I}+(1-z)\frac{\pi_H}{\theta_E}\right)\right)$$

therefore

$$\begin{aligned}
&\frac{\partial rel_net_share}{\partial x_E^*} \\
\approx\ & \left(\left(\frac{1}{2}\pi_H-\pi_L\right)\frac{w_t}{Y_t}+\frac{(\pi_H-\pi_L)}{L}\left(\begin{array}{c}\pi_L+\frac{1}{2}(\pi_H-\pi_L)x_I^* \\ +\left(\frac{1}{2}\pi_H-\pi_L\right)(1-z)x_E^*\end{array}\right)\right)\left(\frac{Y_t}{w_t}\right)^2\frac{1-z}{L_t} \\
\approx\ & \left(\begin{array}{c}\left(\frac{1}{2}\pi_H-\pi_L\right)\left(1-\pi_L-(\pi_H-\pi_L)\left(\frac{\pi_H-\pi_L}{\theta_I}+(1-z)\frac{\pi_H}{\theta_E}\right)\right) \\ +(\pi_H-\pi_L)\left(\pi_L+\frac{1}{2}\frac{(\pi_H-\pi_L)^2}{\theta_I}+\left(\frac{1}{2}\pi_H-\pi_L\right)(1-z)\frac{\pi_H}{\theta_E}\right)\end{array}\right)\left(\frac{Y_t}{w_tL_t}\right)^2(1-z) \\
\approx\ & \left(\left(\frac{1}{2}\pi_H-\pi_L\right)(1-\pi_L)+(\pi_H-\pi_L)\pi_L+\frac{1}{2}\frac{\pi_L(\pi_H-\pi_L)^2}{\theta_I}\right)\left(\frac{Y_t}{w_tL_t}\right)^2(1-z)
\end{aligned}$$

Then $\left(\frac{1}{2}\pi_H-\pi_L\right)(1-\pi_L)+(\pi_H-\pi_L)\pi_L+\frac{1}{2}\frac{\pi_L(\pi_H-\pi_L)^2}{\theta_I}>0$ is a necessary and sufficient condition when L is arbitrarily large under which a decrease in θ_E increases the relative net share.

A.2 Proofs for subsection 2.2.4

From (11), we have: $\frac{\partial x_I^*}{\partial \eta_L}=-\frac{1}{\eta_L^2}\frac{1}{\theta_I}<0$, whereas:

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

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

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

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

Overall, we therefore have:

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

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

A.3 Extensions

A.3.1 Profit sharing between inventor and developer

Here, we assume that once an innovation has been researched, it still needs to be implemented and that this development phase depends on a CEO's effort. Since we are separating the firm owner from the firm manager, we now consider that a firm's owner does not have the outside option of working as a production worker in case her firm does not produce. The economy is still populated by a mass L of workers and a mass 1 of firm owners (who own both the incumbent firm but also the potential entrant firm). For simplicity, the CEO is assumed to be a worker who gets the opportunity to be CEO for a potential entrant or the incumbent in addition to his work as a production workers.

Hence for the owner of an incumbent firm, expected income (net of research spending and CEO wages) is given by:

$$\begin{aligned}\widetilde{\Pi}^{inc}\left(x_I, e_I, R_{I,H}, R_{I,L}\right) &= e_I x_I \left(\pi_H - R_{I,H}\right) Y_t + \left(1 - e_I x_I - (1-z)\, e_E^* x_E^*\right) \pi_L Y_t \\ &\quad - \left(1 - e_I\right) x_I R_{I,L} Y_t - \theta_I \frac{x_I^2}{2} Y_t,\end{aligned}$$

where e_I denotes the likelihood that the CEO succeeds in ensuring that the company implements the new technology—and similarly e_E^* is the equilibrium likelihood that the CEO of an entrant company manages to set-up a new firm. $R_{I,H}Y_t$ is the income that the CEO obtains in case of a success, and $R_{I,L}Y_t$, his income if he fails.

To obtain a success rate e_I, a CEO has to incur a utility effort cost $\psi \frac{e_I^2}{2} Y_t$. The CEOs outside option is 0 (we assume that he can always reject a negative payment). A CEO of an incumbent firm will then solve the following program:

$$\underset{e_I}{Max} \left\{ e_I R_{I,H} Y_t + \left(1 - e_I\right) R_{I,L} - \psi \frac{e_I^2}{2} Y_t \right\}.$$

We then obtain that the constraint $R_{I,L} \geq 0$ will bind. As a result the CEO will choose a success probability:

$$e_I^* = R_{I,H}^* / \psi.$$

This implies that the firm's owner will decide on a payment

$$R_{I,H}^* = \left(\pi_H - \pi_L\right)/2.$$

Therefore, in case of a success, the CEO obtains half of the gains from innovation.

Similarly for an entrant firm owner, we find that her expected income is given by:

$$\widetilde{\Pi}^{ent}\left(x_E, e_E, R_{E,H}, R_{E.L}\right) = (1-z)\, e_E x_E \left(\pi_H - R_{E,H}\right) Y_t - (1-z)\, x_E \left(1 - e_E\right) R_{E,L} Y_t - \theta_E \frac{x_E^2}{2} Y_t.$$

e_E is now the likelihood that the CEO succeeds in setting up a new firm (here we assumed that the CEO effort is undertaken after the innovation has been potentially blocked, this is without loss of generality). As above the constraint that $R_{E,L} = 0$ binds must be satisfied. We then obtain that $e_E^* = R_{E,H}^* / \psi$ as before, which now leads to

$$R_{E,H}^* = \pi_H / 2.$$

Here as well the CEO gets half of the gains from innovation in case of success.[55]

[55] The gains from an innovation for the owner of an entrant firm is $\pi_H Y_t$, while it was $\pi_H Y_t - w_t$ when she

We obtain that as a share of gross output, CEOs income is given by

$$CEO\_share = x_I^* e_I^* R_{I,H} + (1-z)\, x_E^* e_E^* R_{E.H}^* = \frac{1}{\theta_I} \frac{(\pi_H - \pi_L)^4}{16\psi^2} + \frac{(1-z)^2}{\theta_E} \frac{\pi_H^4}{16\psi^2}.$$

Therefore it decreases with both entrant and incumbent innovation costs. As long as the labor force is large enough, top income earners will be the owners and the CEO. As a share of gross output, their joint income (net of innovation costs) will be given by:

$$Top\_share = \pi_H \mu^* + \pi_L (1-\mu^*) - \frac{\theta_E x_E^2}{2} - \frac{\theta_I x_I^2}{2}, \tag{16}$$

where the share of high-mark up sectors satisfies:

$$\mu^* = x_I^* e_I^* + (1-z)\, x_E^* e_E^*.$$

It is then straightforward to show that this top share decreases with the incumbent innovation costs θ_I, whereas the labor share increases with both entrant and incumbent innovation costs. Furthermore, a decrease in entrant innovation cost θ_E shifts income towards top earners relative to workers (i.e. it increases $Top\_share/wage\_share$) if and only if $3\pi_H - 4\pi_L + \pi_L\pi_H + \pi_L \frac{(\pi_H - \pi_L)^4}{8\theta_I\psi^2} > 0$, which is satisfied if profits of innovative firms are large enough relative to the non-innovative ones. Indeed, entrant innovation can potentially reduce the owner share for the same reasons as above. This establishes:

Proposition 4 *A reduction in incumbents innovation costs favors top income earners. A reduction in entrant's innovation costs favors top income earners if and only if* $3\pi_H - 4\pi_L + \pi_L\pi_H + \pi_L \frac{(\pi_H - \pi_L)^4}{8\theta_I\psi^2} > 0$.

Proof. Solving for the innovation decision we obtain that incumbents invest:

$$x_I^* = \frac{1}{\theta_I} \frac{(\pi_H - \pi_L)^2}{4\psi} = \frac{1}{4\psi\theta_I} \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right)^2.$$

Entrants invest

$$x_E^* = \frac{1-z}{4\psi\theta_E} \pi_H^2 = \frac{1-z}{4\psi\theta_E} \left(1 - \frac{1}{\eta_H} \right)^2.$$

We can then express the share of high mark-up sector as:

$$\mu^* = \frac{1}{\theta_I} \frac{(\pi_H - \pi_L)^3}{8\psi^2} + \frac{(1-z)^2}{8\psi^2\theta_E} \pi_H^3.$$

had the outside option of becoming a worker.

Since the wage share is given by

$$\begin{aligned}\frac{w_t L}{Y_t} &= 1-\pi_L-(\pi_H-\pi_L)\,\mu^* \\ &= 1-\pi_L-(\pi_H-\pi_L)\left(\frac{1}{\theta_I}\frac{(\pi_H-\pi_L)^3}{8\psi^2}+\frac{(1-z)^2}{8\psi^2\theta_E}\pi_H^3\right),\end{aligned}$$

both innovation costs increase the labor share of gross output. The top earners share (using (16) and the values for the innovation rates) can then be expressed as:

$$\begin{aligned}Top\_share &= 1-\frac{w_t L}{Y_t}-\left(\frac{(\pi_H-\pi_L)^4}{32\theta_I\psi^2}+\frac{(1-z)^2\,\pi_H^4}{32\theta_E\psi^2}\right), \\ &= \pi_L+\frac{3\,(\pi_H-\pi_L)^4}{32\theta_I\psi^2}+\frac{(1-z)^2\,\pi_H^3\,(3\pi_H-4\pi_L)}{32\psi^2\theta_E}.\end{aligned}$$

Hence we get that Top_share is decreasing in θ_I. Further, we get that

$$\frac{\partial}{\partial\theta_E}\left(\frac{Top\_share}{(w_tL/Y_t)}\right)=-\frac{(1-z)^2\,\pi_H^3}{32\psi^2\theta_E^2}\left(\frac{Y_t}{w_tL}\right)^2\left(3\pi_H-4\pi_L+\pi_L\pi_H+\pi_L\frac{(\pi_H-\pi_L)^4}{8\theta_I\psi^2}\right)$$

Hence an increase in θ_E shifts income towards workers to the detriment of the top earners if $3\pi_H-4\pi_L+\pi_L\pi_H+\pi_L\frac{(\pi_H-\pi_L)^4}{8\theta_I\psi^2}>0$ (which is satisfied if π_H/π_L is large enough). ■

A.3.2 Profit sharing between firm owner and inventor

To distinguish between the firm owner and the innovator we now consider that the set of potential firm owners is given (i.e. there is a mass 1 of capitalists who inherit incumbent firms and can each set up an entrant firm), while innovators are drawn from the population. There is a mass L of potential workers. Workers are identical when in production but differ in the quantity of human capital they can produce in innovation (each worker can produce h units of human capital and h is distributed uniformly over $\left[0,\overline{h}\right]$).

To innovate with probability x an incumbent firm needs to hire $\theta e^2/2$ units of human capital. Similarly an entrant firm needs to hire $\theta e^2/2$ units of human capital.[56] Denoting by v the price of 1 unit of innovative human capital normalized by Y_t, we obtain that there will be a threshold $\widehat{h}$, such that individuals whose h is below $\widehat{h}$ will be production workers and

[56] We assume that the innovation cost is the same for entrants and incumbents. Without this assumption a reduction in entrant's cost could lead to a reduction in overall innovation through its impact on the price of human capital for some extreme parameter assumptions.

those above will be innovators. That threshold obeys

$$\frac{w}{Y} = v\widehat{h}. \tag{17}$$

Solving for the profit maximization problem, we find the optimal innovation rates as:

$$x_I^* = \frac{\pi_H - \pi_L}{\theta v} \text{ and } x_E^* = \pi_H \frac{1-z}{\theta v}, \tag{18}$$

for the incumbent and the entrant respectively. These rates are similar to those in the baseline model, except that they depend on the wage rate v and that the entrant rate does not depend on w (since a firm owner does not have the possibility to become a worker if he fails).

Market clearing for human capital implies:

$$\begin{aligned} \theta\left(\frac{x_I^{*2}}{2} + \frac{x_E^{*2}}{2}\right) &= L\int_{\widehat{h}}^{\overline{h}} h dh \Leftrightarrow \\ (\pi_H - \pi_L)^2 + \pi_H^2 (1-z)^2 &= \theta v^2 L \frac{\overline{h}^2 - \widehat{h}^2}{\overline{h}}. \end{aligned} \tag{19}$$

This equation establishes the demand for innovative human capital as a function of the wage rate and the cost of innovation.

The supply-side equation can be determined by combining (17) with the production labor share equation:

$$\frac{wL\widehat{h}}{Y\overline{h}} = \frac{\mu}{\eta_H} + \frac{1-\mu}{\eta_L},$$

as $L\widehat{h}$ is the labor force in production. We then obtain:

$$vL\frac{\widehat{h}^2}{\overline{h}} = 1 - \pi_L + \frac{\pi_L - \pi_H}{\theta v}\left(\pi_H - \pi_L + \pi_H (1-z)^2\right). \tag{20}$$

Plugging (20) into (19), we obtain that the wage rate for innovative human capital is uniquely defined by:

$$vL\overline{h} = 1 - \pi_L + \pi_L \pi_H \frac{(1-z)^2}{\theta v}. \tag{21}$$

Hence v is decreasing in θ (i.e. the lower is the cost of innovation, the higher is the level of wage per unit of human capital).

As shown below, a decrease in the innovation cost boosts innovation both by entrants and incumbents. In addition, the threshold $\widehat{h}$ decreases, so that when innovation costs go down, more workers end up working as innovators.

Two measures of inequality can be derived here: the share of income going to the firm owners (here we implicitly assume that firm ownership is concentrated at the top of the income distribution) and a measure of top labor income inequality.

The income share of innovators can be derived as:

$$Innov\_share = \int_{\widehat{h}}^{\overline{h}} vLhdh = vL\left(\overline{h}^2 - \widehat{h}^2\right) / \left(2\overline{h}\right). \tag{22}$$

One can show that this expression is decreasing in θ (hence lower innovation costs increase the share of income going to innovators).

We show below that the owner share of GDP must satisfy:

$$\begin{aligned} Owner\_share &= \pi_L(1-\mu) + \pi_H\mu - Innov\_share \\ &= \pi_L + \frac{1}{2\theta v}\left((\pi_H - \pi_L)^2 + (\pi_H - 2\pi_L)\pi_H(1-z)^2\right). \end{aligned} \tag{23}$$

Hence a reduction in innovation costs will increase the owner share of income as long as $(\pi_H - \pi_L)^2 + (\pi_H - 2\pi_L)\pi_H(1-z)^2 > 0$ (the intuition is still that entrant innovations may decrease overall owner's net share of income by suppressing the rents of an incumbent). If firms' owner are disproportionately concentrated in the top of the income distribution, this predicts that a reduction in innovation will increase top income inequality.

The share of labor income going to the individuals above some ratio $\widetilde{h}/\overline{h}$ can be expressed as

$$\begin{aligned} TopLincome(\widetilde{h}) &= \frac{\int_{\widetilde{h}}^{\overline{h}} vhdh}{\frac{w}{Y}\frac{\widehat{h}}{\overline{h}} + \int_{\widehat{h}}^{\overline{h}} vhdh} = \frac{\overline{h}^2 - \widetilde{h}^2}{\widehat{h}^2 + \overline{h}^2} \text{ if } \widetilde{h} \geq \widehat{h} \\ &= 1 - \frac{\frac{w}{Y}\frac{\widetilde{h}}{\overline{h}}}{\frac{w}{Y}\frac{\widehat{h}}{\overline{h}} + \int_{\widehat{h}}^{\overline{h}} vhdh} = 1 - \frac{2\widehat{h}\widetilde{h}}{\widehat{h}^2 + \overline{h}^2} \text{ if } \widetilde{h} \leq \widehat{h}. \end{aligned}$$

In both cases, *TopLincome* is decreasing in $\widehat{h}$ and therefore also in innovation costs. One can then prove the following proposition.

Proposition 5 *A reduction in innovation costs leads to an increase in innovation, an increase in top labor income inequality and an increase in the owners' share of income if* $(\pi_H - \pi_L)^2 + (\pi_H - 2\pi_L)\pi_H(1-z)^2 > 0$.

Proof: Using (21) we have:

$$\frac{dv}{d\theta} = \frac{v}{\theta}\frac{-\pi_L\pi_H\frac{(1-z)^2}{\theta v^2}}{L\overline{h} + \pi_L\pi_H\frac{(1-z)^2}{\theta v^2}}.$$

Hence we get:

$$\frac{d(\theta v)}{d\theta} = v\frac{L\overline{h}}{L\overline{h} + \pi_L\pi_H\frac{(1-z)^2}{\theta v^2}} > 0.$$

Using (18) we then obtain that both entrant innovation x^* and incumbent innovation x_I^* decrease with θ. Differentiating (19) we get:

$$\begin{aligned}
\frac{d\widehat{h}}{d\theta} &= \frac{\overline{h}^2 - \widehat{h}^2}{2\theta}\left(1 + 2\frac{\theta}{v}\frac{dv}{d\theta}\right) \\
&= \frac{\overline{h}^2 - \widehat{h}^2}{2\theta}\frac{L\overline{h} - \pi_L\pi_H\frac{(1-z)^2}{\theta v^2}}{L\overline{h} + \pi_L\pi_H\frac{(1-z)^2}{\theta v^2}} \\
&= \frac{\overline{h}^2 - \widehat{h}^2}{L\overline{h} + \pi_L\pi_H\frac{(1-z)^2}{\theta v^2}}\frac{1-\pi_L}{2\theta v} > 0,
\end{aligned}$$

where we used (21) to obtain the latter equality.

Using (19) in (22), we obtain that the share of income that goes to innovators is given by:

$$Innov\_share = \frac{(\pi_H - \pi_L)^2 + \pi_H^2(1-z)^2}{2\theta v},$$

which is decreasing in θ since θv is increasing in θ.

To compute the owner share we use the previous equation and (18) in (23) to obtain:

$$\begin{aligned}
Owner_share &= \pi_L + (\pi_H - \pi_L)(x_I^* + (1-z)x_E^*) - Innov_share \\
&= \pi_L + (\pi_H - \pi_L)\left(\frac{\pi_H - \pi_L}{\theta v} + (1-z)\pi_H\frac{1-z}{\theta v}\right) - \frac{(\pi_H - \pi_L)^2 + \pi_H^2(1-z)^2}{2\theta v} \\
&= \pi_L + \frac{1}{2\theta v}\left((\pi_H - \pi_L)^2 + (\pi_H - 2\pi_L)\pi_H(1-z)^2\right).
\end{aligned}$$

Therefore the owner share is increasing in θ if and only if $(\pi_H - \pi_L)^2 + (\pi_H - 2\pi_L)\pi_H(1-z)^2 > 0$, which establishes the Proposition.

B Online Appendix B

Table B1: Top 0.1% and Top 0.01% income share and innovation from incumbents and entrants

Dependent variable	Top 0.1% Income Share			Top 0.01% Income Share		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation by Entrants	0.017**		0.016**	0.016		0.016
	(2.12)		(1.98)	(1.45)		(1.39)
Innovation by Incumbents		0.035***	0.035***		0.047***	0.048***
		(3.39)	(3.44)		(3.39)	(3.48)
Gdppc	-0.240***	-0.215***	-0.229***	-0.358***	-0.322***	-0.336***
	(-3.31)	(-3.07)	(-3.22)	(-3.43)	(-3.18)	(-3.28)
Popgrowth	4.006***	4.159***	4.058***	5.446***	5.694***	5.554***
	(3.06)	(3.35)	(3.24)	(2.93)	(3.23)	(3.13)
Sharefinance	1.149***	1.340***	1.394***	1.222**	1.491**	1.569***
	(2.81)	(2.99)	(3.41)	(2.12)	(2.34)	(2.72)
Gvtsize	-2.616***	-2.426***	-2.312***	-3.491***	-3.177***	-3.049***
	(-3.93)	(-3.74)	(-3.52)	(-3.75)	(-3.49)	(-3.32)
Unemployment	-0.328	-0.576	-0.607	-0.731	-1.076	-1.125
	(-0.54)	(-0.98)	(-1.03)	(-0.88)	(-1.34)	(-1.40)
R^2	0.781	0.784	0.785	0.724	0.729	0.730
Observations	1224	1224	1224	1224	1224	1224

Notes: The table presents estimates of the number of citations received within a five-year window per inhabitants on the top 0.1% and top 0.01% income share of state income. We consider two different types of innovation, innovation by entrants as defined by assignees that first patented less than 3 years ago and innovation by incumbents as defined by assignees that first patented more than 3 years ago: columns (1) to (3) use the top 0.1% income share and columns (4) to (6) use the top 0.01% income share. Both innovation measures and dependent variables are taken in log. Time span: 1980-2004 due to availability of the disambiguition database on assignees and inventors from Lai *et al.* (2014). Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B2: Top 1% income share and innovation with clustered standard errors

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.019	0.030***	0.025*	0.031**	0.013**	0.008*
	(0.95)	(2.71)	(1.78)	(2.08)	(2.45)	(1.75)
Gdppc	-0.058	-0.091*	-0.090*	-0.089*	-0.078*	-0.077
	(-1.24)	(-1.89)	(-1.74)	(-1.75)	(-1.65)	(-1.60)
Popgrowth	0.148	-0.100	-0.117	-0.083	-0.139	-0.134
	(0.12)	(-0.07)	(-0.08)	(-0.06)	(-0.09)	(-0.09)
Sharefinance	0.274	0.433	0.386	0.397	0.391	0.321
	(0.73)	(1.26)	(1.11)	(1.15)	(1.14)	(0.96)
Gvtsize	0.119	0.184	0.086	0.101	0.193	0.115
	(0.22)	(0.33)	(0.16)	(0.19)	(0.34)	(0.21)
Unemployment	-0.422	-0.645	-0.595	-0.588	-0.624	-0.563
	(-0.64)	(-0.86)	(-0.79)	(-0.80)	(-0.83)	(-0.76)
R^2	0.908	0.915	0.914	0.915	0.915	0.914
Observations	1785	1632	1632	1632	1632	1632

Notes: The table presents estimates of different measures of innovation on the top 1% income share of state income. We consider different measures of innovation which are all lagged by 2 years and standardized by state population: column (1) uses the number of patents, column (2) uses the number of citations received within a five-year window, column (3) uses the number of claims, column (4) uses the number of patent weighted by their generality index, column (5) uses the number of patents belonging to the top 5% most cited in the year and column (6) uses the number of patents belonging to the top 1% most cited in the year. All these measures as well as the dependent variable are taken in log. Time span: 1976-2011 for column (1) and 1976-2008 for columns (2) to (6). Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with heteroskedasticity robust standard errors clustered at the state level. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B3: Innovation and various measures of inequality based on different income shares

Dependent variable	Top 10%	Top 5%	Top 1%	Top 0.5%	Top 0.1%	Top 0.01%
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation	0.019***	0.021***	0.030***	0.044***	0.052***	0.065***
	(4.29)	(3.97)	(3.53)	(4.61)	(4.12)	(3.56)
Gdppc	-0.053**	-0.038	-0.091	-0.105**	-0.121*	-0.175*
	(-2.02)	(-1.18)	(-1.52)	(-2.06)	(-1.88)	(-1.89)
Popgrowth	0.415	0.407	-0.100	0.979	1.459	2.198
	(0.99)	(0.89)	(-0.10)	(1.19)	(1.32)	(1.41)
Sharefinance	0.499***	0.489***	0.433**	0.823***	0.544	0.171
	(4.22)	(3.07)	(2.24)	(2.74)	(1.22)	(0.27)
Gvtsize	-0.692***	-0.805***	0.184	-1.684***	-1.973***	-2.241***
	(-3.60)	(-3.68)	(0.55)	(-4.67)	(-4.21)	(-3.37)
Unemployment	-0.222	-0.554***	-0.645	-0.948**	-1.135**	-1.645**
	(-1.24)	(-2.64)	(-1.48)	(-2.41)	(-2.13)	(-2.17)
R^2	0.821	0.873	0.915	0.892	0.892	0.865
Observations	1632	1632	1632	1632	1632	1632

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on various measures of inequality: column (1) uses the top 10% income share, column (2) uses the top 5%, column (3) uses the top 1% income share, column (4) uses the top 0.5% income share, column (5) uses the top 0.1% income share and column (6) uses the top 0.01% income share. The innovation measure has been lagged by 2 years and is taken in log. The dependent variable is also in log in all columns. Time span: 1976-2008. Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B4: Top 1% income share and innovation by entrants and incumbents - alternative definition of entrants

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation		Patents			Cit5	
Innovation by Entrants	0.034**		0.035**	0.013*		0.010
	(2.39)		(2.39)	(1.86)		(1.49)
Innovation by Incumbents		0.009	-0.002		0.012	0.008
		(0.74)	(-0.16)		(1.49)	(1.01)
Gdppc	-0.108	-0.129*	-0.107	-0.176***	-0.192***	-0.183***
	(-1.54)	(-1.85)	(-1.50)	(-2.58)	(-2.72)	(-2.70)
Popgrowth	0.898	0.717	0.896	0.075	-0.166	0.059
	(0.81)	(0.64)	(0.81)	(0.06)	(-0.11)	(0.04)
Sharefinance	0.428**	0.485**	0.423**	0.552**	0.721***	0.591**
	(2.25)	(2.52)	(2.14)	(2.29)	(3.01)	(2.36)
Gvtsize	0.170	0.128	0.170	-0.529	-0.505	-0.507
	(0.46)	(0.33)	(0.46)	(-1.21)	(-1.12)	(-1.16)
Unemployment	-0.303	-0.440	-0.295	-0.242	-0.417	-0.280
	(-0.66)	(-0.92)	(-0.63)	(-0.46)	(-0.74)	(-0.54)
R^2	0.881	0.878	0.881	0.829	0.828	0.830
Observations	1479	1479	1479	1224	1224	1224

Notes: The table presents estimates of two different measures of innovation lagged by two years (number of patents and number of citations within a five-year window per inhabitants) on the top 1% income share of state income. We consider two different types of innovation, innovation by entrants as defined by assignees that first patented less than 5 years ago and innovation by incumbents as defined by assignees that first patented more than 5 years ago: columns (1) to (3) use the number of patents, columns (4) to (6) use the number of citations within a five-year window. All these measures as well as the dependent variable are taken in log. Time span: 1981-2008 for columns (1) to (3) and 1981-2004 for columns (4) to (6) due to availability of the disambiguition database on assignees and inventors from Lai *et al.* (2014). Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with auto-correlation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B5: FIRST STAGE AND REDUCED FORM REGRESSIONS

Dependent variable	Cit5	Top 1%	Cit5	Top 1%	Cit5	Top 1%
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Appropriation Committee	0.099***	0.017**			0.041*	0.018**
	(3.88)	(2.26)			(1.67)	(2.02)
Spillover			4.707***	0.573***	4.594***	0.554***
			(10.26)	(3.73)	(9.92)	(3.51)
Gdppc	0.719***	-0.089	0.959***	-0.007	1.050***	-0.019
	(2.77)	(-1.51)	(3.04)	(-0.10)	(3.32)	(-0.28)
Popgrowth	-0.244	-0.053	3.970	1.834*	4.506*	2.123*
	(-0.10)	(-0.05)	(1.61)	(1.76)	(1.79)	(1.95)
Sharefinance	-4.004***	0.248	-2.377***	0.970***	-2.289***	0.926***
	(-5.43)	(1.32)	(-2.89)	(5.00)	(-2.68)	(4.70)
Gvtsize	-3.183**	-0.433	0.690	0.792	2.796	0.454
	(-2.00)	(-1.14)	(0.37)	(1.54)	(1.44)	(0.81)
Unemployment	4.400***	-0.473	7.730***	0.036	7.816***	0.036
	(3.65)	(-1.06)	(6.36)	(0.08)	(6.34)	(0.08)
Highways	-0.107***	0.012				0.021**
	(-3.28)	(1.23)				(2.13)
Military	-0.042***	0.004			-0.037***	0.004
	(-4.43)	(0.92)			(-3.35)	(0.70)
Spatial Corr	No	No	Yes	Yes	Yes	Yes
R^2	0.879	0.918	0.880	0.851	0.883	0.858
Observations	1600	1600	1326	1326	1300	1300

Notes: The table presents the regressions results of our instruments on the innovation variable (measured by the number of citations received within a five-year window) (columns (1), (3) and (5)) and the results of our instruments directly on the dependent variable (the share of income held by the richest 1%) in other columns. Columns (1) and (2) use the state number of senators with a seat on the Senate appropriation committee, columns (3) and (4) use the spillover instruments at three different lags and columns (5) and (6) use all instruments. The lags between the depend variable and the instruments are set to match the corresponding 2 stage regressions: 3 years for column (1), 5 years for column (2), 1 year for columns (3), 3 years for column (4), 3 and 1 years for column (5) and 5 and 3 years for column (6). DC is removed from the sample in columns (1), (2), (5) and (6) because it has no senators. All the dependent variables and the spillover instrument are taken in log. Time Span: 1977-2008 for columns (1) and (2) and 1983-2008 for columns (3) to (6). Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. Innovation as well as the top 1% income share are taken in log. Control for spatial correlation involves adding two additional controls for demand shocks as explained in subsection 6.1. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B6: Innovation and various measures of inequality - IV results

Dependent Variable	Top 1%	Avgtop	Top 10 %	Overall Gini	G99	Atkinson
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation	0.172**	0.034	0.054	-0.010	-0.027	0.045
	(2.03)	(1.22)	(1.32)	(-0.41)	(-0.90)	(1.29)
Gdppc	-0.212**	-0.067**	-0.079**	0.027	0.041	0.037
	(-2.21)	(-2.14)	(-2.06)	(1.04)	(1.25)	(1.01)
Popgrowth	-0.011	0.486	0.425	-0.325*	-0.374	0.361
	(-0.01)	(1.14)	(0.90)	(-1.76)	(-1.61)	(1.19)
Sharefinance	0.936**	0.279**	0.558***	0.058	-0.142	0.429**
	(2.28)	(2.01)	(2.88)	(0.50)	(-1.01)	(2.28)
Gvtsize	0.114	-0.168	-0.804***	0.402**	0.810***	-0.303
	(0.24)	(-0.91)	(-3.75)	(2.30)	(3.72)	(-1.50)
Unemployment	-1.229*	-0.075	-0.342	-0.071	0.122	-0.297
	(-1.79)	(-0.35)	(-1.31)	(-0.43)	(0.56)	(-1.34)
Highways	0.030**	0.003	0.011	0.011***	0.011**	0.011
	(2.35)	(0.71)	(1.58)	(2.99)	(2.43)	(1.53)
Military	0.011*	-0.004**	-0.001	-0.004**	-0.005**	-0.000
	(1.85)	(-2.03)	(-0.53)	(-2.05)	(-2.36)	(-0.22)
R^2	0.897	0.438	0.819	0.873	0.749	0.930
1^{st} stage F-stat	14.64	14.64	14.64	14.64	14.64	14.64
Observations	1600	1600	1600	1600	1600	1600

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on various measures of inequality: column (1) uses the top 1% income share, column (2) uses the average size of percentiles 2 to 10 in the income distribution, column (3) uses the 10% income share, column (4) uses the gini coefficient, column (5) uses the gini coefficient excluding the first percentile of the income distribution and column (6) uses the Atkinson index with a coefficient of 0.5. The innovation measure has been lagged by 2 years and is taken in log. The dependent variable is also in log in all columns. Time span: 1977-2008. Variable description is given in Table 3.

Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that seat on the appropriation committee. DC is removed from the sample in all columns because it has no senators. The lag between the instrument and the endogeneous variable is set to 3 years. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B7: Top 1% income share and innovation at different lags - IV results

Dependent variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Lag of innovation	2 years	3 years	4 years	5 years	6 years
Innovation	0.209**	0.194**	0.164*	0.115	0.082
	(2.20)	(2.05)	(1.91)	(1.45)	(0.94)
Gdppc	-0.284**	-0.271**	-0.255**	-0.246**	-0.183*
	(-2.52)	(-2.41)	(-2.33)	(-2.08)	(-1.79)
Popgrowth	0.533	1.127	1.007	1.315	1.355
	(0.40)	(0.83)	(0.77)	(1.00)	(1.08)
sharefinance	1.265***	1.129***	0.922***	0.757**	0.628**
	(2.83)	(2.69)	(2.63)	(2.41)	(2.24)
Gvtsize	0.218	0.513	0.377	0.252	0.260
	(0.43)	(0.89)	(0.69)	(0.49)	(0.46)
Unemployment	-1.620*	-1.387*	-1.226	-0.864	-0.538
	(-1.81)	(-1.68)	(-1.60)	(-1.28)	(-0.87)
Highways	0.033**	0.028**	0.023*	0.013	0.002
	(2.34)	(2.10)	(1.78)	(1.04)	(0.17)
Military	0.012*	0.008	0.007	0.003	-0.000
	(1.66)	(1.30)	(1.13)	(0.55)	(-0.00)
R^2	0.897	0.886	0.867	0.834	0.817
1^{st} stage F-stat	15.56	15.08	15.72	16.18	12.12
Observations	1400	1400	1400	1400	1400

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on the top 1% income share at different lags column (1) uses a two-year lag between the measure of innovation and the dependent variable, column (2) uses three-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Time span: 1981-2008. Variable description is given in Table 3. Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that seat on the appropriation committee. DC is removed from the sample in all columns because it has no senators. The lag between the instrument and the endogeneous variable is set to 3 years. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B8: Regression of innovation on Top 1% income share using only the second instrument

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.206***	0.122***	0.151***	0.167***	0.099***	0.155***
	(3.43)	(3.50)	(3.46)	(3.44)	(3.31)	(2.96)
Gdppc	-0.165*	-0.123	-0.139	-0.117	-0.074	-0.131
	(-1.83)	(-1.41)	(-1.52)	(-1.29)	(-0.84)	(-1.29)
Popgrowth	1.808*	1.351	1.365	1.323	1.297	1.801
	(1.65)	(1.21)	(1.27)	(1.20)	(1.10)	(1.36)
Sharefinance	0.966***	1.259***	1.152***	1.201***	1.449***	1.502***
	(3.86)	(4.99)	(4.75)	(4.87)	(4.69)	(4.03)
Gvtsize	0.555	0.708	0.481	0.540	1.311**	1.944**
	(1.19)	(1.47)	(0.98)	(1.09)	(2.11)	(2.27)
Unemployment	-1.038*	-0.905	-0.804	-0.793	-1.185*	-1.421*
	(-1.71)	(-1.54)	(-1.43)	(-1.41)	(-1.77)	(-1.75)
R^2	0.793	0.831	0.829	0.827	0.806	0.686
1st stage F-stat	81.04	102.62	103.49	93.11	64.98	24.27
Observations	1478	1326	1326	1326	1326	1326

Notes: The table presents estimates of different measures of innovation lagged by two years on the top 1% income share of state income: column (1) uses the number of patents, column (2) uses the number of citations received within a five-year window, column (3) uses the number of claims, column (4) uses the number of patents weighted by their generality index, column (5) uses the number of patents belonging to the top 5% most cited in the year and column (6) uses the number of patents belonging to the top 1% most cited in the year. All these measures as well as the dependent variable are taken in log. Time span: 1983-2011 for columns (1) 1983-2008 for columns (2) to (6). Variable description is given in Table 3.
Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by a measure of spillover as described in section 6.1. The lags between the instruments and the endogeneous variable is set to 1 year. Control for spatial correlation involves adding two additional controls for demand shocks as explained in subsection 6.1. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B9: Robustness 2: financial sector and natural resources - IV results

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation	0.172**	0.153*	0.173**	0.201*	0.173**	0.174**
	(1.99)	(1.92)	(2.02)	(1.74)	(2.05)	(2.02)
Gdppc	-0.211**	-0.199*	-0.215**	-0.219**	-0.199**	-0.214**
	(-2.12)	(-1.91)	(-2.21)	(-2.15)	(-1.97)	(-2.22)
Popgrowth	-0.009	-0.004	-0.045	0.047	-0.051	-0.022
	(-0.01)	(-0.00)	(-0.04)	(0.04)	(-0.04)	(-0.02)
Sharefinance	0.940**	1.064***	0.943**	1.010**	0.921**	0.945**
	(2.38)	(3.31)	(2.27)	(2.07)	(2.07)	(2.27)
Gvtsize	0.115	0.059	0.065	0.069	0.201	0.075
	(0.24)	(0.14)	(0.14)	(0.15)	(0.36)	(0.16)
Unemployment	-1.225*	-1.693**	-1.221*	-1.136*	-1.269*	-1.235*
	(-1.74)	(-2.33)	(-1.79)	(-1.78)	(-1.86)	(-1.79)
Highways	0.030**	0.021	0.030**	0.032**	0.029**	0.031**
	(2.42)	(1.35)	(2.35)	(2.22)	(2.36)	(2.37)
Military	0.011*	0.011*	0.011*	0.012*	0.011*	0.011*
	(1.80)	(1.81)	(1.85)	(1.82)	(1.91)	(1.84)
RemunFinance	-0.000					
	(-0.08)					
EFD				-0.660		
				(-1.01)		
Oil					-0.001	
					(-0.14)	
Mining					0.761	
					(1.04)	
R^2	0.897	0.907	0.896	0.890	0.897	0.897
1^{st} stage F-stat	14.04	14.53	14.28	10.56	15.08	14.65
Observations	1600	1472	1600	1600	1600	1600

Notes: The table presents estimates of the number of citations received with a five year-window per inhabitants lagged by two years on the top 1% income share of state income: in column (1) we control for average compensation in the financial sector, in column (2), NY, CT, DE and MA (the state with the largest financial sectors) are dropped from the dataset, in column (3), finance-related patents have been removed, in column (4) we control for financial dependence in the state as explained in section 6.2, in column (5) we control for the size of oil and mining sectors and in column (6) oil-related patents have been removed in the count of citations. Time Span: 1978-2008. Variables *Oil* and *NaturalRessource* measure the share of oil related and natural resources extraction activities in GDP, variable *RemunFinance* measures the compensation per employee in the financial sector and variable *EFD* measures the financial dependence of innovation. Time span 1976-2008. Other variables description is given in Table 3.
Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that seat on the appropriation committee. DC is removed from the sample in all columns because it has no senators. The lag between the instrument and the endogeneous variable is set to 3 years. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B10: Robustness 3A: controlling for industry composition - OLS results

Dependent variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Innovation	0.037***	0.029***	0.030***	0.039***	0.026***
	(3.51)	(3.40)	(3.31)	(4.24)	(3.33)
Gdppc	-0.082	-0.092	-0.090	-0.081	-0.089
	(-1.39)	(-1.53)	(-1.50)	(-1.34)	(-1.49)
Popgrowth	-0.121	-0.100	-0.109	-0.363	-0.112
	(-0.12)	(-0.10)	(-0.11)	(-0.37)	(-0.11)
Sharefinance	0.411**	0.426**	0.425**	0.401**	0.424**
	(2.18)	(2.21)	(2.21)	(2.16)	(2.20)
Gvtsize	0.219	0.178	0.169	0.074	0.166
	(0.65)	(0.53)	(0.50)	(0.22)	(0.50)
Unemployment	-0.624	-0.645	-0.624	-0.791*	-0.647
	(-1.43)	(-1.48)	(-1.43)	(-1.82)	(-1.48)
Size of Sector:					
Computer and Electronic				-0.235***	
				(-3.46)	
Chemistry				0.195	
				(1.62)	
Electrical Component				0.535*	
				(1.88)	
R^2	0.915	0.915	0.915	0.917	0.915
Observations	1632	1632	1632	1632	1632

Notes: The table presents estimates of innovation as measured by the number of citations received within a five-year window on the size of the top 1% income share. Innovation is lagged by two years. We look at the effect of industry composition: column (1), excludes patents from the computer sectors (NAICS: 334), column (2) excludes patents from the pharmaceutical sectors (NAICS: 3254) and column (3) excludes patents from the electrical equipment sectors (NAICS: 335), column (4) adds the share of three sectors as additional controls and column (5) excludes citations to patents belonging to three highly exporting sectors: Transportation, Machinery and Electrical Machinery. The size of a sector (see column (4)) is defined as the share of GDP from the corresponding sector. Time span: 1976-2008. Variable description is given in Table 3.
Panel data OLS regressions with state and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B11: Robustnesess 3B: controlling for industry composition - IV results

Dependent variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Innovation	0.328*	0.174**	0.183**	0.168**	0.160**
	(1.80)	(2.02)	(2.02)	(2.08)	(2.00)
Gdppc	-0.197**	-0.226**	-0.215**	-0.173**	-0.207**
	(-1.97)	(-2.23)	(-2.20)	(-2.09)	(-2.21)
Highways	0.036**	0.030**	0.030**	0.020*	0.029**
	(2.11)	(2.32)	(2.35)	(1.78)	(2.29)
Military	0.018*	0.012*	0.012*	0.009*	0.011*
	(1.92)	(1.86)	(1.88)	(1.71)	(1.80)
Popgrowth	-0.238	0.003	-0.048	-0.494	-0.027
	(-0.20)	(0.00)	(-0.04)	(-0.44)	(-0.02)
Sharefinance	1.129**	0.939**	0.952**	0.729**	0.946**
	(2.03)	(2.27)	(2.26)	(2.22)	(2.26)
Gvtsize	0.716	0.109	0.088	-0.186	0.119
	(0.90)	(0.23)	(0.19)	(-0.43)	(0.25)
Unemployment	-1.413*	-1.268*	-1.157*	-1.267*	-1.307*
	(-1.73)	(-1.80)	(-1.75)	(-1.94)	(-1.82)
Size of Sector:					
Computer and Electronic				-0.501**	
				(-2.48)	
Chemistry				0.240*	
				(1.73)	
Electrical Component				0.052	
				(0.12)	
R^2	0.845	0.890	0.891	0.896	0.890
1^{st} stage F-stat	6.35	14.14	14.93	13.34	14.05
Observations	1548	1548	1548	1548	1548

Notes: The table presents estimates of innovation as measured by the number of citations received within a five-year window on the size of the top 1% income share. Innovation is lagged by two years. We look at the effect of industry composition: column (1), excludes patents from the computer sectors (NAICS: 334), column (2) excludes patents from the pharmaceutical sectors (NAICS: 3254) and column (3) excludes patents from the electrical equipment sectors (NAICS: 335), column (4) adds the share of three sectors as additional controls and column (5) excludes citations to patents belonging to three highly exporting sectors: Transportation, Machinery and Electrical Machinery. The size of a sector (see column (4)) is defined as the share of GDP from the corresponding sector. Time span: 1976-2008. Variable description is given in Table 3.
Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that seat on the appropriation committee. DC is removed from the sample in all columns because it has no senators. The lag between the instrument and the endogeneous variable is set to 3 years. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table B12: Robustness 4: controlling for agglomeration effect - OLS and IV results.

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation	0.022**	0.021**	0.020**	0.196*	0.216*	0.232*
	(2.27)	(2.14)	(2.02)	(1.90)	(1.85)	(1.79)
Gdppc	-0.151**	-0.152**	-0.153**	-0.208**	-0.197**	-0.191**
	(-2.34)	(-2.36)	(-2.38)	(-2.48)	(-2.46)	(-2.43)
Popgrowth	-0.300	-0.302	-0.302	-0.241	-0.244	-0.242
	(-0.29)	(-0.30)	(-0.30)	(-0.21)	(-0.21)	(-0.21)
Sharefinance	0.370*	0.371*	0.375*	0.829**	0.828**	0.818**
	(1.85)	(1.86)	(1.87)	(2.14)	(2.11)	(2.08)
Gvtsize	-0.013*	-0.013*	-0.013*	-0.007	-0.005	-0.005
	(-1.89)	(-1.92)	(-1.92)	(-0.81)	(-0.62)	(-0.52)
Unemployment	-0.603	-0.605	-0.611	-1.065*	-1.025*	-0.986*
	(-1.42)	(-1.43)	(-1.44)	(-1.70)	(-1.68)	(-1.65)
Highways				0.031**	0.031**	0.032**
				(2.36)	(2.32)	(2.30)
Military				0.014*	0.016*	0.016*
				(1.88)	(1.86)	(1.83)
Agglo	0.007	0.008	0.009	-0.046	-0.068	-0.084
	(1.27)	(1.17)	(1.22)	(-1.42)	(-1.45)	(-1.44)
R^2	0.916	0.916	0.916	0.895	0.891	0.887
1^{st} stage F-stat				13.97	12.35	10.86
Observations	1632	1632	1632	1600	1600	1600

Notes: The table presents estimates of innovation as measured by the number of citations received within a five-year window on the size of the top 1% income share. Innovation is lagged by two years. We look at the effect of agglomeration as captured by the variable *Agglo*. *Agglo* is the log of the number of firms in the most (columns 1 and 4), the two most (columns 2 and 5), and the three most (columns 3 and 6) innovative sectors for each state and year. Time span: 1976-2008. Variable description is given in Table 3.

Panel data OLS (columns 1 to 3) and IV 2SLS (columns 4 to 6) regressions with state and year fixed effects. DC is removed from the sample in columns (4), (5) and (6) because it has no senators. Innovation is instrumented by the number of senators that seat on the appropriation committee. The lag between the instrument and the endogeneous variable is set to 3 years. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.