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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.

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1 Introduction

It is widely acknowledged that the past decades have experienced a sharp increase in top income inequality – particularly in developed countries.[1] Yet, no consensus has been reached as to the main underlying factors behind this increase. In this paper we argue that, in a developed country like the US, innovation is certainly one such factor. For example, in the list of the wealthiest individuals per US state, compiled by *Forbes Magazine*, 11 out of 50 are listed as inventors of a US patent and many more manage or own firms that patent. This suggests these individuals have earned high incomes over time in relation to innovation. More importantly, patenting and top income inequality in the US and other developed countries have followed a parallel evolution. Thus, Figure 1 shows the number of granted patents and the top 1% income share in the US since the 1960s: Up to the early 1980s, neither variable exhibits a trend, but since then both variables experience parallel upward trends.

More closely related to our analysis in this paper, Figure 2 examines 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 significantly 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 particularly affected occupations that appear to be closely related to innovation such as entrepreneurs, engineers, scientists, as well as managers.[2]

We first develop a Schumpeterian growth model where growth results from quality-improving innovations that can be made in each sector, either by the incumbent or by a potential entrant. Facilitating innovation or entry increases the entrepreneurial share of income and spurs social mobility through creative destruction. The model predicts that: (i) entrants' and incumbents' innovation increase top income inequality; (ii) entrants' innovation increases social mobility; (iii) entry barriers lower the positive effects of entrants' innovations on top income inequality and social mobility. Yet, higher mark-ups for non-innovating incumbents can lead to higher top income inequality and lower innovation.

We start our empirical analysis by exploring correlations between innovation and various measures of inequality using OLS regressions. Since our innovation measures build on patent data, we focus on appropriated innovation which is more likely to affect income inequality. Our results can be summarized as follows. First, the top 1% income share in a given state

[1] Piketty and Saez (2003) documents the sharp increase in top income inequality in the US, while books such as Goldin and Katz (2009), Deaton (2013) and Piketty (2014) have spurred a worldwide interest for income and wealth inequality.

[2] Bakija et al. (2008) find that the income share of the top 1% in the US 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 (Frydman and Papanikolaou, 2015), and firm owners (Aghion et al., 2018).

in a given year, is positively and significantly correlated with the state's rate of innovation. Second, innovation is less positively, or even negatively, correlated with broader measures of inequality which do not emphasize top incomes, like the Gini coefficient, as suggested by Figure 3. Next, the correlation between innovation and the top 1% income share weakens at longer lags. Finally, it is dampened in states with high lobbying intensity.

To make the case that the correlation between innovation and top inequality at least partly reflects a causal effect of innovation on top incomes, we instrument for innovation using data on the United States Senate Committee on Appropriations (following Aghion et al., 2009). We argue that the composition of the appropriation committee affects the allocation of earmarks across all states, and in turn affects patenting and innovation in the states. We then regress top income inequality on innovation instrumented by the composition of the appropriation committee. All the main OLS results are confirmed by the corresponding IV regressions. Our IV results imply that an increase of 1% in the number of patents increases the top 1% income share by 0.2%, and the effects of a 1% increase in the citation-based measures are of comparable magnitude. We also build a second instrument for state innovation which relies on knowledge spillovers from other states. Although the two instruments are uncorrelated, we find very similar effects.

Next, we calibrate the main parameters of the model with our regression results, and use our calibrated model to reproduce the regressions of the paper. We find a very good fit between the OLS and IV regressions coefficients on the one hand, and the coefficients estimated from the calibrated model on the other hand.

Finally, we analyze the relationship between innovation and social mobility using cross-sectional regressions at the commuting zone (CZ) level. We find that: (i) innovation is positively correlated with upward social mobility (as suggested in Figure 4); (ii) this correlation is driven by entrant innovators, and dampened in CZs with high lobbying intensity.

The analysis in this paper relates to several strands of literature. First, we contribute to the endogenous growth literature (Romer, 1990; Aghion and Howitt, 1992; Aghion et al., 2014; Akcigit, 2017) by looking explicitly at the effects of innovation on top income shares and social mobility.

Second, our work adds to the empirical literature on inequality and growth (see for instance Barro, 2000 who studies the link between overall growth and inequality measured by the Gini coefficient, Forbes, 2000 or 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 the United States. We contribute to this literature by showing that innovation-led growth is a source of top income inequality.

Third, a large literature on skill-biased technical change aims at explaining the increase in labor income inequality since the 1970s.[3] While this literature focuses on the *direction* of

[3]Katz and Murphy (1992) and Goldin and Katz (2009) have shown that technical change has been skill-biased in the 20^{th} century. Lloyd-Ellis (1999), Acemoglu (1998, 2002) or Hémous and Olsen (2016)

innovation and broad measures of labor income inequality (such as the skill-premium), we focus on the rise of the top 1% and its relation with the *rate* of innovation.

Fourth, our paper relates to recent literature on inequality and firm dynamics. 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 their owners and managers. Similarly, Gabaix and Landier (2008) show that the increase in firm size can account for the increase in 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 productivity across firms, and therefore in firms' size and pay.[4]

Finally, worthy of mention is a new set of papers on innovation and individuals' income. Frydman and Papanikolaou (2015) find that innovation and executive pay are positively correlated (Balkin et al., 2000 find the same result in high-tech industries). Aghion et al. (2018) use data from Finland to show that innovation increases an individual innovator's probability to make it to the higher income brackets, and innovation has an even larger effect on firm owners' income. Bell et al. (2017) find that the most successful innovators see a sharp rise in income. Akcigit et al. (2017) find a positive correlation between patenting intensity and social mobility across the United States over the past 150 years.

Most closely related to our paper, Jones and Kim (2017) 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 could result from incumbent innovation), and creative destruction by entrants. The former increases top income inequality whereas the latter reduces it.[5] 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. Both papers have in common: (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".[6]

The remainder of the paper is organized as follows. Section 2 outlays a Schumpeterian

endogenize the direction of technical change. Krusell et al. (2000) relate the increase in the skill premium with the increase in the equipment stock. Several papers (Aghion and Howitt, 1998; Caselli, 1999 and Aghion et al., 2002) argue that General Purpose Technologies increase labor income inequality.

[4]Our analysis is also consistent with Hall et al. (2005), Blundell et al. (1999) or Bloom and Van Reenen (2002) who find that innovation has a positive impact on market value.

[5]In Jones and Kim (2017) entrants innovation reduces income inequality because it affects incumbents' efforts so that an exogenous increase in entrant innovation affects inequality only if it is anticipated by incumbents. Moreover, their model predicts a positive correlation between growth and inequality in the short-run (due to a scale effect) and a negative correlation only in the long-run.

[6]Indeed, we show that entrant innovation is positively associated with social mobility. Moreover, while we find that incumbent and entrant innovation contribute to a comparable extent to increasing the top 1% income share, additional regressions in Table C1 of Appendix C suggest that incumbent innovation contributes more to increasing the top 0.1% or top 0.01% than entrant innovation.

model to guide our empirical analysis. Section 3 describes our state panel data on inequality and innovation. Section 4 presents our OLS results. Section 5 explains our IV instrument and shows our IV results. Section 6 reports robustness tests. Section 7 performs our calibration exercise. Section 8 looks at the relationship between innovation and social mobility. Section 9 concludes. An online appendix with additional theoretical and empirical results, and a more detailed description of the data and the calibration, can be found at this link.

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.

2.1 Baseline model

We consider a discrete time economy populated by a continuum of individuals of measure M. At any point in time a mass $M/(1+L)$ of individuals are firm owners and the rest, $ML/(1+L)$, are workers (so $L \geq 1$ is the ratio of workers to entrepreneurs). Each individual lives for one period. Every period, a new generation is born and individuals 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:

$$\ln Y_t = \int_0^{M/(1+L)} \frac{1+L}{M} \ln y_{it} di, \tag{1}$$

where y_{it} is the amount of intermediate input i used for final production at date t. The number of product lines $M/(1+L)$ scales up with population size (as in Howitt, 1999). Therefore, the final good sector spends the same amount, $\tilde{Y}_t$, on all intermediates:

$$p_{i,t} y_{it} = \tilde{Y}_t = \frac{1+L}{M} Y_t \text{ for all } i. \tag{2}$$

Each intermediate i is produced by a monopolist who faces a competitive fringe, using a linear production function:

$$y_{it} = q_{it} l_{it}, \tag{3}$$

where l_{it} is the amount of labor hired to produce i at t, and q_{it} is labor productivity.

2.1.2 Innovation

Productive innovation Whenever there is a new "productive 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. Both entrants and incumbents can undertake productive innovations. We denote their respective productive innovation rates by $x_{E,i}$ and $x_{I,P,i}$ in line i. At the end of period t, other firms can partly imitate the (now 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 from η_H to η_L with $1 < \eta_L < \eta_H$.

Defensive innovation The incumbent may instead undertake a "defensive innovation" which does not increase productivity (i.e. $q_{i,t} = q_{i,t-1}$) but ensures maintaining a technological lead of η_H. That is, a defensive innovation prevents potential competitors from using a technology which is too close to the incumbent's. We denote by $x_{I,D,i}$ the defensive innovation rate of incumbents. Again, in the absence of a new innovation in period $t+1$, the technological lead of the incumbent shrinks back to η_L.

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.[7]

To innovate with probability $x_{E,i}$ a potential entrant needs to spend

$$C_{E,t}(x) \equiv \frac{\theta_E x_{E,i}^2}{2} \tilde{Y}_t;$$

while to undertake productive innovation at rate $x_{I,P,i}$ and defensive innovation at rate $x_{I,D,i}$, an incumbent needs to spend

$$C_{I,t}(x) \equiv \frac{\theta_I \left(x_{I,P,i} + x_{I,D,i}\right)^2}{2} \tilde{Y}_t.$$

The parameters θ_E and θ_I capture R&D productivity for entrants and incumbents respectively, and the innovation cost functions scale up with per capita GDP.

Introducing the dichotomy between *productive* and *defensive* innovations allows us to capture the difference between patents and "true innovation": namely, some patents are used to protect rents without contributing much to productivity growth. Indeed, a growing number of defensive patents may explain why the observed increase in patenting does not

[7] 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.

seem to be fully reflected in productivity growth.[8]

Finally, we assume that an incumbent producer who 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).

2.1.3 Timing of events

For simplicity, we rule out the possibility that both entrant and incumbent innovate in the same period.[9] We also assume that in each line i a single potential entrant is drawn from the mass of workers' offspring. The timing of each period is summarized in Figure 5.

2.2 Solving the model

To solve the model, we first compute the entrepreneurs' and workers' income shares and the rate of social mobility at given innovation rates. We then endogeneize innovation.

2.2.1 Income shares and social mobility for given innovation rates

In this subsection we assume that in all sectors, at any date t, potential entrants innovate at some exogenous rate x_{Et} and incumbents innovate at some exogenous rate x_{It}, knowing that a share ϕ_t of their innovations is productive. Limit pricing in any intermediate sector i implies that the price charged by the incumbent producer is equal to the technological lead η_{it} times the marginal cost $MC_{it} = w_t/q_{i,t}$, hence:

$$p_{i,t} = w_t \eta_{it}/q_{i,t}, \tag{4}$$

where $\eta_{i,t} \in \{\eta_H, \eta_L\}$. Innovation allows the technological leader to (temporarily) increase the mark-up from η_L to η_H.

Equations (2) and (4) allow us to express equilibrium profits in sector i at time t as

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

Thus equilibrium profits only depend upon mark-ups and aggregate output. Profits are higher whenever the technological leader has recently innovated (no matter the type of

[8] An alternative or complementary explanation is that productivity growth from creative destruction may be mismeasured (see Aghion et al., 2017).

[9] Hence, in a given sector, innovations by the incumbent and the entrant are not independent events. This assumption is a discrete time approximation of a continuous time model of innovation. It can be microfounded as follows: Every period there is a mass 1 of ideas, and only one idea is successful. Research efforts x_E and x_I represent the mass of ideas that a firm investigates. Firms can observe each other actions, so that in equilibrium they look for different ideas (as long as θ_E and θ_I are large enough to ensure $x_E^* + x_I^* < 1$).

innovation, productive or defensive), namely:

$$\Pi_{H,t} = \pi_H \tilde{Y}_t > \Pi_{L,t} = \pi_L \tilde{Y}_t \text{ with } \pi_H \equiv \frac{\eta_H - 1}{\eta_H} \text{ and } \pi_L \equiv \frac{\eta_L - 1}{\eta_L}.$$

We can now derive the expressions for the income shares of workers and entrepreneurs. Let μ_t denote the fraction of high-mark-up sectors (i.e. with $\eta_{it} = \eta_H$) at date t. Then, the gross share of income earned by an entrepreneur at time t is equal to:

$$entrepreneur\_share_t = \frac{\mu_t \Pi_{H,t} + (1 - \mu_t) \Pi_{L,t}}{\tilde{Y}_t} = 1 - \frac{\mu_t}{\eta_H} - \frac{1 - \mu_t}{\eta_L}. \tag{5}$$

This entrepreneur share is "gross" in the sense that it does not include any potential monetary costs of innovation (and similarly all of our share measures are expressed as functions of total output instead of net income—see Appendix A.2 for the expressions of net shares).

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

$$wages\_share_t = \frac{w_t L}{\tilde{Y}_t} = \frac{\mu_t}{\eta_H} + \frac{1 - \mu_t}{\eta_L}. \tag{6}$$

We restrict attention to the case where $\eta_L - 1 > 1/L$, which ensures that $w_t < \Pi_{L,t}$ for any value of μ_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 a measure of inequality within top-earners).

Since mark-ups are larger in sectors with new technologies, aggregate income shifts from workers to entrepreneurs in relative terms whenever the share of product lines with new technologies μ_t increases. By the law of large numbers this share is equal to the probability of an (unblocked) innovation in any intermediate sector. Formally, we have:

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

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

Finally, we measure intergenerational upward social mobility by the probability Ψ_t that the offspring of a worker becomes a business owner. This occurs only if an entrant innovates and is not blocked by the incumbent, so that:

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

Social mobility is decreasing in entry barrier intensity z, and it is increasing in the entrant's innovation intensity x_{Et} but less so with higher entry barrier intensity z. In other words, entry barriers increase the persistence of innovation rents. This yields:

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

Moreover, while all innovations reduce the wage *share*; productive innovations increase the wage *level* and defensive innovations reduce it.[10] Finally, the entrepreneurial income share is independent of innovation intensities in previous periods, therefore a temporary increase in innovation only leads to a temporary increase in the entrepreneurial income share. Once imitation occurs, the gains will be equally shared by workers and entrepreneurs.

2.2.2 Endogenous innovation

We now turn to the endogenous determination of the innovation rates of entrants and incumbents.[11] The offspring of the previous period's incumbent solves the following problem:

$$\max_{x_{I,P},\, x_{I,D}} \left\{ \begin{array}{c} (x_{I,P} + x_{I,D})\, \pi_H + (1 - x_{I,P} + x_{I,D} - (1-z)\, x_E^*)\, \pi_L \\ + (1-z)\, x_E^* \frac{w_t}{\tilde{Y}_t} - \theta_I \frac{(x_{I,P}+x_{I,D})^2}{2} \end{array} \right\} \tilde{Y}_t.$$

Therefore, the heir of an incumbent can collect profits from the inherited firm, but innovating will increase profits. Incumbents are indifferent between protective and defensive innovations, so that only the total incumbent innovation rate $x_I = x_{I,P} + x_{I,D}$ is determined in equilibrium (any share of productive innovation ϕ is an equilibrium).[12] The equilibrium incumbent innovation rate satisfies:

$$x_{I,t} = x_I^* = \frac{\pi_H - \pi_L}{\theta_I} = \left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)\frac{1}{\theta_I}, \tag{9}$$

which decreases with the incumbent R&D cost parameter θ_I.

A potential entrant in sector i solves the following problem:

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

---

[10] By plugging (2) and (4) in (1) one obtains: $w_t = (1+L)\, Q_t / \left(M \eta_H^{\mu_t} \eta_L^{1-\mu_t}\right)$, where $Q_t \equiv \exp \int_0^{M/(1+L)} \frac{1+L}{M} \ln q_{it} di$ is the quality index. Its law of motion is given by $Q_t = Q_{t-1} \eta_H^{(\phi x_{It} + x_{Et}(1-z))}$. Therefore, for given technology level at time $t-1$, the equilibrium wage is given by

$$w_t = \frac{1+L}{M} Q_{t-1} \eta_L^{\phi x_{It} + x_{Et}(1-z) - 1} \left(\frac{\eta_L}{\eta_H}\right)^{(1-\phi) x_{It}}.$$

This shows that the rate of productive innovations $(\phi x_{It} + x_{Et}\,(1-z))$ increases the contemporaneous level of wage, while the rate of defensive innovations $((1-\phi)\, x_{It})$ decreases it.

[11] Throughout this section, we implicitly assume that θ_I and θ_E are sufficiently large that the aggregate innovation rate satisfies: $x_E^* + x_{I,P}^* + x_{I,D}^* < 1$.

[12] It would be easy to modify the model such that ϕ is uniquely determined: for instance by assuming that $x_{I,P}$ and $x_{I,D}$ are not perfect substitute in the innovation cost function.

as a new entrant chooses its innovation rate with the outside option of being a production worker who receives wage w_t. Using equation (6), taking first order condition, and using our assumption that $w_t < \Pi_{L,t}$ (so that entrants innovate in equilibrium), we obtain:

$$x_{E,t} = x_E^* = \left(\pi_H - \frac{1}{L}\left[\frac{\mu_t}{\eta_H} + \frac{1-\mu_t}{\eta_L}\right]\right)\frac{1-z}{\theta_E}. \tag{10}$$

Since in equilibrium $\mu^* = x_I^* + (1-z)\,x_E^*$, the equilibrium entrant innovation rate satisfies:

$$x_E^* = \frac{\left(\pi_H - \frac{1}{L}\frac{1}{\eta_L} + \frac{1}{L}\left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)x_I^*\right)(1-z)}{\theta_E - \frac{1}{L}(1-z)^2\left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)}, \tag{11}$$

so that 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.[13]

Therefore, a reduction in either entrants' or incumbents' R&D costs increases innovation, thereby increasing the share of high mark-up sectors and the gross entrepreneurs' share of income. As higher entry barriers dampen the positive correlation between the entrants' innovation rate and the share of high mark-up sectors, 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 entry barriers. We have thus established (proof in Appendix A.1):

Proposition 2 *An increase in incumbent R&D productivity leads to an increase in the incumbent innovation rates x_I^*. An increase in incumbent or entrant R&D productivity leads to an increase in the entrant innovation rates x_E^* and therefore the entrepreneur share and the social mobility rate, but less so for higher entry barriers z.*

Here we refer to the entrepreneurial share of income gross of the innovation costs, which amounts to treating those as private utility costs. The results can be extended to the entrepreneurial share net of innovation costs as shown in Appendix A.2.[14]

[13] The entrant innovation intensity x_E^* increases with x_I^* as more innovation by incumbents lowers the wage share 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.

[14] A reason not to include innovation costs is that in practice entrepreneurial incomes are typically generated after these costs are sunk, even though in our model we assume that innovation expenditures and entrepreneurial incomes occur within the same period.

2.2.3 Extensions

Shared rents from innovation. In the model so far, all rents from innovation accrue to an individual entrepreneur who fully owns her firm. Yet, our regressions will capture the overall effect of innovation on top income inequality, and in particular the fact that, in the real world, the returns from innovation are shared among several actors (inventors, developers, CEOs, firms' owners, financiers,...). We show this formally in Appendix A.4 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.

CES production function. We show that our results are robust to the case where (1) is replaced by a CES production function in Appendix A.5.

2.3 From theory to the empirics

2.3.1 Entrepreneurial share and top income share

In our empirical analysis, we shall regress top income shares on innovation. Our innovation measure is based on the number of patents per capita, which is the empirical counterpart of the innovation rate μ in the model (the model assumes that the total number of innovations scales up with population size). Our focus so far has been on the entrepreneurial share of income instead of the top income share. Yet, top incomes are earned by entrepreneurs (or, more generally, individuals associated with innovation) as long as L is sufficiently large. To solve for the top $\alpha\%$ income share, one must consider three cases.

Case 1: $\alpha/100 < \mu/(1+L)$: The top $\alpha\%$ earners consist only of entrepreneurs who have innovated successfully. Then:

$$Top\_\alpha\%\_share = \frac{\alpha(1+L)}{100}\left(1-\frac{1}{\eta_H}\right).$$

In this case a marginal change in innovation has no impact on the top $\alpha\%$ share.[15]

Case 2: $\mu/(1+L) < \alpha/100 < 1/(1+L)$: Then the top $\alpha\%$ earners consist of all entrepreneurs who have innovated successfully, plus a fraction of those who have not:

$$Top\_\alpha\%\_share = \mu\left(\frac{1}{\eta_L}-\frac{1}{\eta_H}\right)+\frac{\alpha(1+L)}{100}\left(1-\frac{1}{\eta_L}\right). \tag{12}$$

Thus, in this case an increase in the number of (non-blocked) innovations leads to an increase

[15]This result depends on our assumption that all innovations have the same size η_H. If one were to relax this assumption and allows for a continuous gap, one would get that an increase in innovation quality would affect the top income share at all percentiles.

in the top $\alpha\%$ share of income. In particular, we get that:

$$\frac{\partial \ln Top\_\alpha\%\_share}{\partial \ln \mu} = \frac{\mu}{Top\_\alpha\%\_share} \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right) > 0. \tag{13}$$

If the number of patents per capita is proportional to the number of successful innovations, this expression corresponds to the elasticity of the top $\alpha\%$ share with respect to the number of patents per capita. For a given innovation rate, this elasticity is decreasing in α, decreasing in the mark-up of non-innovators η_L, and increasing in the mark-up of innovators η_H.

Case 3: $1/(1+L) < \alpha/100$. Then the top $\alpha\%$ earners consist of all entrepreneurs, plus some workers. In that case we get:

$$Top\_\alpha\%\_share = \mu \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right) \left(1 - \left(\frac{\alpha(1+L)}{100} - 1 \right) \frac{1}{L} \right) + 1 - \frac{1}{\eta_L} + \left(\frac{\alpha(1+L)}{100} - 1 \right) \frac{1}{L} \frac{1}{\eta_L},$$

so that

$$\frac{\partial \ln Top\_\alpha\%\_share}{\partial \ln \mu} = \frac{\mu}{Top\_\alpha\%\_share} \left(\frac{1}{\eta_L} - \frac{1}{\eta_H} \right) \left(1 - \left(\frac{\alpha(1+L)}{100} - 1 \right) \frac{1}{L} \right) > 0.$$

Here as well, an increase in the number of (non-blocked) innovations μ leads to an increase in the top $\alpha\%$ share of income. Additionally, the corresponding elasticity is increasing in η_H, decreasing in η_L, and decreasing in α for a given innovation rate.

2.3.2 From inequality to innovation

Although we have emphasized the effect of innovation on top income shares, our 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 entrepreneurs' income share for a given innovation rate (see (5)) as well as innovation incentives. Thus, a higher η_H increases incumbents' (9) and (11) 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, thereby increasing the entrepreneur share for a given innovation rate. Yet, it decreases incumbents' innovation rate because their net reward from innovation is lower. Under mild conditions (e.g. if $\theta_E \geq (1-z)\theta_I/L$), this leads to a decrease in the total innovation rate (see Appendix A.3). Yet, for sufficiently high R&D costs, the overall impact of a higher η_L on the entrepreneur share remains positive. Therefore a higher η_L can contribute to a negative correlation between innovation and the entrepreneur share, leading to a downward bias on the innovation coefficient in an OLS regression of top income inequality on innovation.

2.3.3 Our IV strategy through the lens of our model

Our IV strategy below will rely on shocks which reduce the costs of innovation. In terms of our model, suppose that entrant and incumbent innovation costs are respectively equal to $\theta_E = \theta\Theta_E$ and $\theta_I = \theta\Theta_I$, where exogenous reductions in θ are driven by our instrument. The causal effect of our instrument on innovation will be captured by the expression

$$\frac{d\mu_t}{d\theta} = (1-z)\frac{dx_E^*}{d\theta} + \frac{dx_I^*}{d\theta}.$$

2.4 Predictions

The main predictions from the above theoretical discussion can be summarized as follows:

- *Innovation by both entrants and incumbents increases top income inequality;*
- *The effect of innovation on income inequality is stronger on higher income brackets;*
- *Innovation by entrants increases social mobility;*
- *Entry barriers lower the positive effect of entrants' innovation on top income inequality and on social mobility.*

Further, the 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 the decline of the labor share (e.g. see Elsby et al., 2013 and Karabarbounis and Neiman, 2014).

3 The empirical framework

In this section we present our measures of inequality and innovation and the databases used to compute these measures. We follow with a description of our estimation strategy.

3.1 Data and measurement

Our core empirical analysis is carried out at the state level, within the United States. Our dataset starts in 1976, a time range imposed by the availability of patent data.

3.1.1 Inequality

The data on state-level top 1% income shares 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 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), and the Gini Index (definition of these measures can be found in Table 1). Although these data are available from 1916 to 2013, we restrict attention to the period after 1976. We establish a balanced panel of 51 states (as we include the District of Columbia) over a time period of 36 years. In 2013, the three states with the highest top 1% income share were New-York, Connecticut, and Wyoming with 31.8%, 30.8% and 29.6%, respectively. Iowa, Hawaii and Alaska were the states with the lowest top 1% income share (11.7%, 11.4% and 11.1%, respectively). In every state, the top 1% income share has increased between 1975 and 2013. The unweighted mean value was around 8.4% in 1975, reaching 20.4% in 2007 before decreasing to 17.1% in 2013. In addition, the heterogeneity in top income shares across states was larger in the recent period than during the 1970s, with a cross-state coefficient of variation multiplied by 2.2 between 1976 and 2013. Wyoming, Idaho, Montana and South Dakota experienced the fastest growth in the top 1% income share during this time period; while DC, Connecticut, New Jersey and Arkansas experienced the slowest growth.

Income in this database is the adjusted gross income from the IRS. This is a broad measure of pre-tax and pre-transfer income which covers wages, entrepreneurial income and capital income (including realized capital gains). While it is not possible to decompose total income between its various sources with this dataset, the World Top Income Database (Alvaredo et al., 2014) gives the composition of the top 1% and top 10% income shares at the federal level. On average between 1976 and 2013, wage income represented 59.3% (respectively 76.9%) and entrepreneurial income was 22.8% (respectively 12.9%) of the total income earned by the top 1% (respectively top 10%). 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 by the extension of the model in Appendix A). Yet, the overrepresentation of entrepreneurial income relative to wage income in the top 1% suggests that our baseline model captures an important aspect of top income inequality.

3.1.2 Innovation

A first measure of innovation for each state and each year is the *flow number of patents per capita* in that state and year.[16] For patents granted from 1976, the United States Patent and Trademark Office (USPTO) provides information on the state of residence of the patent *inventors*, the date of application of the patent, and a link to every citing patent. We associate a patent with the state of their inventors, and, when patents have coinventors living in different states (around 15% of cases), we split them across states according to the number of inventors.[17] A patent is also associated with an *assignee* that owns the right to the patent. Usually, the assignee is the firm employing the inventor or, for independent inventors, the inventor herself. In most cases, the location of the inventor and assignee coincide (the

[16]In line with the model, we consider the flow of patents per capita instead of just the flow of patents, to normalize for the size of the state and control for the mechanical fact that larger states innovate more.

[17]In line with the literature, we restrict attention to utility patents which cover 90% of all patents and protect inventions and exclude design patents and plant patents.

correlation is greater than 95%).[18] Nevertheless, we show later that our baseline results are robust in allocating each patent to the state of its assignees (see Appendix C, Table C3).

We associate a patent with its application year, which is the year when the provisional application is considered complete by the USPTO, and a filing date is set. Because we consider patents that were ultimately granted by 2014, our data suffer from a truncation bias due to the time lag between application and grant. The USPTO estimated in the end of 2012 that patent application data should be considered 95% complete for applications filed in 2004.[19] By the same logic, we consider that by the end of 2014, our patent data are essentially complete up to 2006. For the years between 2006 and 2009, we correct for truncation bias using the distribution of time lags between the application and granting dates. This extrapolates the number of patents by states following Hall et al. (2001). We stop our analysis in 2009 because of the smaller number of patents beyond then.

The annual flow of patent per capita has been multiplied by 1.6, on average, between 1976 and 2009 (around 70% of that increase is due to an increase in the number of inventors). Yet, simply counting the number of patents granted by their application date is a crude measure of innovation, as patents reflect innovations of very heterogeneous quality. The USPTO database provides exhaustive information on patent citations, which we use to compute five additional measures of quality-adjusted innovation rates:

- *Patents per capita weighted by the number of citations within 5 years*: This variable measures the number of citations received within 5 years of the application date. This number is corrected to account for the different propensity to cite across sectors and time and for the truncation bias in citations following Hall et al. (2001). We consider this series reliable up to 2006.

- *Patents per capita in the top 5% (or 1%) most cited in a given year.* For each application year, this variable only counts patents among the top 5% (or 1%) most cited in the following five years. For the same reasons as above, these series are stopped in 2006. As argued in Abrams et al. (2013), such variables are useful if there are nonlinearities between the value of a patent and the number of forward citations.

- *Patents per capita weighted by the number of their claims.* The number of claims captures the *breadth* of a patent (see Lerner, 1994, and Akcigit et al., 2016).

- *Patents per capita weighted by their generality.* Following Hall et al. (2001), we compute the generality of a patent as one-minus the Herfindahl index of the technological classes

[18] Delaware and DC are the states for which the inventor's address is more likely to differ from the assignee's address for fiscal reasons. See Table C2 in Appendix C for more detail.

[19] 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."*

that cite the patent, where technological classes are defined at the 4-digit level of the International Patent Classification (IPC).[20]

These measures of innovation display consistent trends: Thus the four most innovative states between 1975 and 1990 according to the number of patents per capita are also the most innovative according to the number of (5-year-) citations weighted patents per capita. Similarly, for the period 1990-2010. From Figure 2, Idaho, Washington, Oregon and Vermont experienced the fastest growth in innovation, while West Virginia, Oklahoma, Delaware and Arkansas experienced the slowest. More statistics and details are given in Tables 2 and 3 as well as in Appendix C, Table C4.

As pointed out previously, patenting *per se* may not fully reflect true innovation, but also partly appropriation. Hence, the distinction between "productive" and "defensive" innovation in our model above. Moving to more qualitative measures of innovation such as citations, breadth, or generality, partially addresses this concern.

3.1.3 Control variables

Regressing top income shares on innovation raises concerns which can be addressed by adding suitable controls. First, the state-specific business cycle likely has direct effect on innovation and top income share. Second, to a significant extent, top income share groups likely include individuals employed by the financial sector (see, for example, Philippon and Reshef, 2012, or Bell and Van Reenen, 2014). In turn, the financial sector is sensitive to business cycles and also may affect innovation directly. To address these two concerns, we control for the business cycle via the unemployment rate; and for the location specialization index of the financial sector (defined as the share of total GDP accounted for by the financial sector in the state, divided by the same share at the national level). 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 can be found in the Bureau of Economic Analysis (BEA) regional accounts and in the Bureau of Labor Statistics (BLS).

Taxation may also create a spurious correlation between top income inequality and innovation, as lower taxes could lead to both higher top incomes and higher innovation through the migration of top inventors (see Moretti and Wilson, 2017 for US migration of star inventors and Akcigit et al., 2016 for international migration). To address this concern we control for the maximum marginal tax rates on labor and realized capital gains in the state,

[20]Formally, the generality index G_{it} of a patent i with application date t is defined as $G_{it} = 1 - \sum_{j=1}^{J}\left(\frac{s_{j,t,t+5}}{\sum_{j=1}^{J} s_{j,t,t+5}}\right)^2$, where $s_{j,t,t+5}$ is the number of citations received from other patents in IPC 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.

using data from the NBER TAXSIM project. Agglomeration is also a potential geographical determinant of both innovation and inequality, as we discuss in Appendix B.2.

3.2 Estimation strategy

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

$$\log(y_{it}) = \beta_1 \log(innov_{i,t-2}) + \beta_2 X_{it} + B_i + B_t + \varepsilon_{it}, \tag{14}$$

where y_{it} is the measure of inequality, B_i a state-fixed effect, B_t a year-fixed effect, $innov_{i,t-2}$ innovation in year $t-2$,[21] and X a vector of control variables. We discuss further dynamic aspects of our data in Section 4.6. By including state- and time-fixed effects, we eliminate permanent cross-state differences in inequality and aggregate changes.[22] Therefore we are studying the relationship between the differential growth in innovation across states with the differential growth in inequality. Since we take logs in both innovation and inequality, the coefficient β_1 measures the elasticity of inequality with respect to innovation.

Because 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 run the regressions corresponding to equation (14) for t between 1978 and 2011 when measuring innovation by the number of patents, the number of claims, or the generality weighted patent count. We run regressions from 1978 and 2008 when measuring innovation, using the citation based 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 state, we find no significant autocorrelation after two lags. Therefore, we choose a bandwidth equal to 2 years in the Newey-West standard errors.[23]

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

[22] 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 .758. Similarly when we regress innovation measured by citations in a 5-year window, on its one year lagged value, we find a precisely estimated coefficient of .812.

[23] 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 C5 in Appendix C.

4 Results from OLS regressions

In this section we present the results from OLS regressions of income inequality on innovation. We first look at the correlation between top income inequality and innovation, before extending the analysis to other measures of inequality. Next, we look separately at incumbent versus entrant innovation and analyze the role of lobbying. Finally, we see how top income inequality correlates with innovation at different lags.

4.1 Innovation and top income inequality

Table 4 regresses (the log of) the top 1% income share on (the log of) our measures of innovation with a 2-year lag. The relevant variables are defined in Table 1. Column 1 uses the number of patents per capita as a measure of innovation, column 2 uses the number of citations per capita in a 5-year window, column 3 uses the number of claims per capita, column 4 uses the generality weighted patent count per capita, and columns 5 and 6 use the number of patents among the top 5% and top 1% most cited patents in the year, divided by the state's population.[24]

These tables show that the coefficient of innovation is always positive and significant. The coefficient on the citations weighted number of patents is larger than that on the raw number of patents. This suggests the more highly cited patents are associated with the top 1% income share which are more likely to correspond to true innovations. This is in line with Hall et al. (2005), who show an extra citation increases the market share of the firm that owns the patent. 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, using the coefficients in column 1 of Table 4, and the summary statistics in Table 3, we can compare the magnitude of the correlations between either innovation or the importance of the financial sector, and the top 1% income share. Thus, a one standard deviation increase in our measure of innovation is associated with a 2.4-point increase in the top 1% income share. A one standard deviation increase in the importance of the financial sector is associated with a 1.9-point increase in the top 1% income share. Since the OLS estimates are likely to be biased, we refer to section 5.1 for further discussion of the magnitude of our effects based on IV regressions.[25]

[24] In Appendix C, Table C6, we consider the number of citations per capita in a 5 year window as our measure of innovation and introduce control variable progressively.

[25] In line with the mechanism of the model we find a positive correlation between top income inequality and the share of entrepreneurs as presented in Table C7 of Appendix C.

4.2 Innovation and other measures of inequality

We now run the same regression as before but using broader measures of inequality as a dependent variable: The top 10% income share; the Gini coefficient; and the Atkinson index. Moreover, with data on the top 1% income share, and following Atkinson and Piketty (2007) and Alvaredo (2011), we derive an estimate for the Gini coefficient of the remaining 99% of the income distribution, which we denote by $G99$ as:

$$G99 = (G - top1) / (1 - top1),$$

where G is the global Gini and *top1* is the top 1% income share. To determine whether the effect of innovation on inequality is 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%. Denoting by *top10* the top 10% income share, this average share is equal to:

$$Avgtop = (top10 - top1) / 9.$$

Table 5 shows the results obtained when regressing these measures of inequalities on innovation. We present results for the citation variable but we get similar results when using other measures of innovation. Column 1 reproduces the results for the top 1% income share. Column 2 uses the top 10% income share, column 3 uses the *Avgtop* measure, column 4 uses the overall Gini coefficient, column 5 uses the Gini coefficient for the bottom 99% of the income distribution, and column 6 uses the Atkinson Index with parameter 0.5. We see that innovation: (a) is most significantly positively correlated with the top 1% income share; (b) is less positively correlated with the top 10% income share; (c) is not significantly correlated with the Gini index, and is negatively correlated with the bottom 99% Gini. Moreover, the Atkinson index with coefficient equal to 0.5 is positively correlated with innovation.

Finally, in Table 6 we use more concentrated top income share measures, namely the top 0.01, 0.05 and 0.1% income shares. The correlation between innovation and top income share increases as we move up to the income distribution, with the coefficient of innovation reaching 0.087 for the top 0.01% income share.

4.3 Entrants and incumbents innovation

To distinguish between incumbent and entrant innovation in our data, we rely on the inventor and assignee disambiguation work of the PatentViews initiative managed by the USPTO.[26] 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 is less than 3 years (alternatively we use a 5-year threshold). We then aggregate the number of "entrant patents" as well

[26] Accessible online at http://www.patentsview.org. In addition, here and only here, we focus on patents issued by firms and we have removed patents from public research institutes or independent inventors.

as the number of "incumbent patents" at the state level from 1980.[27] According to our definition, 17% of patents from 1980 to 2014 correspond to an entrant innovation (versus 23.7% when we use the 5-year lag threshold instead). Entrant patents have more citations than incumbent patents: For example in 1980, each entrant patent has 11.4 citations on average, whereas an incumbent patent only has 9.5 citations, which supports the view that entrant patents correspond to more radical innovations (see Akcigit and Kerr, 2017).

Table 7 presents the results from regressing the log of the top 1% income share on 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 (see Table C8 in Appendix C for the 5-year threshold instead). The coefficients on both entrant and incumbent innovation are always positive and significant, although the two coefficients are not statistically different from one another.

4.4 Lobbying as a dampening factor

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

Measuring lobbying expenditures at the state level is not straightforward since lobbying activities often occur nationwide. To obtain a local measure of lobbying, we use national sectoral variations in lobbying, with state-level variations in sectoral composition, a strategy similar to the seminal work by Bartik (1991). More specifically, the OpenSecrets project[28] provides yearly sector-specific lobbying expenditures at the national level from 1998. We then proxy for state-level lobbying intensity by computing a weighted average of sectoral level lobbying expenditures (3-digit NAICS sectors), with weights corresponding to sector shares in the state's total employment from the US Census Bureau.[29]

We then run an OLS regression of the top 1% income share on innovation, the aforementioned lobbying intensity measure, and the interaction between the two. This is done separately for entrant innovation (columns 1 to 3 of Table 8) and for incumbent innovation (columns 4 to 6 of Table 8). The results are in line with the predictions of our model:

[27] We start in 1980 to reduce the risk of wrongly considering a patent to be an "entrant patent" because of the truncation issue at the beginning of the time period. In addition, to look for the first patent of each assignee, we consider patents with an application year prior to 1976 (but granted afterwards).

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

[29] More precisely, we first build a proxy for the lobbying intensity in sector k in state i at year t, denoted $Lob(i,k,t)$, using national level sectoral expenditures $Lob(.,k,t)$. We then average these state-sector level measures at the state level to obtain a proxy for state-level lobbying expenditures $Lob(i,.,t)$:

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

where $emp(i,k,t)$ denotes industry k's share of employment in state i at date t (with $1 \leq k \leq K$ and $1 \leq i \leq I$). Our measure of lobbying intensity is computed as the logarithm of $Lob(i,.,t)$.

We find a negative interaction term between entrant innovation and lobbying intensity. In other words, the effect of entrant innovation on top income inequality is dampened when the lobbying intensity increases.

4.5 Timing between innovation and top income

One may question the choice of two-year lagged innovation in the right-hand side of our baseline regression equation. Here is how we converged on it: First, two years is roughly the average time between a patent application and its grant date at the USPTO and most patent offices (in the US, the average lag is 2.6 years from 1976 to 2005, it has slightly increased over time, the complete distribution of this lag is plotted in Figure C1 of Appendix C). Second, evidence points at inventors' income moving up immediately after, or before the patent is granted. Thus, using Finnish individual data on patenting and wage income, Toivanen and Väänänen (2012) find an immediate jump in inventors' wages after patent grant. Using EPO data, Depalo and Addario (2014) find that inventors' wages peak around the time of the patent application. While using USPTO data, Bell et al. (2017) show that the earnings of inventors start increasing before the filing date of the patent application. In the same vein, Frydman and Papanikolaou (2015) find that executive pay goes up during the year when the patent is granted.

That inventors' incomes (and more generally innovation-related incomes) should increase even before the patent is granted, is not so surprising. First, patent applications are mostly organized and supervised by firms which 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. Second, firms may sell a product embedding an innovation before the patent has been granted, thereby already appropriating some of the profits from the innovation. Similarly, the shareholders of an innovating firm can sell their stocks and benefit from the innovation before the patent is granted. Third, already at the application stage, patenting is associated with easier access to VC financing or with a higher likelihood of an IPO for start-up firms, both of which may translate into a higher income for the innovating entrepreneur (e.g. see Hsu and Ziedonis, 2008 or Haussler et al., 2014).

4.6 Top income inequality and innovation at different time lags

Here we test the robustness of our results to alternative lags for innovation. Table 9 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. To have comparable estimates based on a similar number of observations, we restrict the time period to 1981-2008. This table shows that the coefficient on lagged innovation remains significant for up to 6 years, but its magnitude decreases with the lag. The effect eventually disappears as we increase the lag beyond 6 years. This finding is consistent with the view that innovation should have a temporary effect on top income inequality due to imitation and/or creative destruction, in line with the Schumpeterian model in Section 2.[30]

4.7 True innovation or simply appropriation?

The correlations we found so far are between top income inequality and patenting per capita. Patenting per capita is only a proxy for true innovation for two key reasons. First, a significant proportion of innovations are not patented. Such innovations still induce increases in rents and therefore in top income inequality; yet, to the extent that the benefits from non-patented innovations are less easily appropriated, the relationship between non-patented innovations and top income inequality is likely weaker than that between patented innovation and top income inequality. Second, some patents are geared towards preserving incumbents' monopoly rents without contributing significantly to productivity growth (the "defensive innovations" of our model in Section 2). Two considerations lead us to believe that the correlation we found between patenting and inequality also involves true innovation: (a) While defensive innovations are typically made by incumbents, we showed that entrant innovation is also positively correlated with top income inequality; (b) The correlation between innovations and top income inequality remains strong when we consider more qualitative measures of innovation (number of citations, patent breadth, generality,..), which suggests that it goes beyond a pure appropriation effect of patents.[31]

4.8 Summary

The results of the OLS regressions performed in this section are broadly in line with the predictions of our model, namely: (i) innovation measured by the flow or quality of patenting per capita, is positively correlated with top income inequality; (ii) innovation is not significantly correlated with broader measures of inequality; (iii) the correlation between innovation and top income inequality is temporary; (iv) top income inequality is positively correlated with both entrant and incumbent innovation; (v) the correlation between entrant innovation and top income inequality is lower in states with higher lobbying intensity.

5 Endogeneity of innovation and IV results

In this section, we argue that the positive correlation between innovation and top income inequality at least partly reflects a causal effect of innovation on top income. To reach

[30] This prediction is likely to be heterogeneous across sectors. For example, the effect is no longer significant after 4 years when restricting to NAICS 336: Transport Equipment, whereas it is still significant after 6 years in sector NAICS 334: Computer and electronic products.

[31] In particular, if: (i) changes over time in the share of true innovations among patented innovations remain constant across states; (ii) true patented innovations lead to the same rents as "defensive innovations", then our regressions exactly capture the correlation between top income inequality and true patented innovations.

this conclusion we must account for the possible endogeneity of our innovation measure. Endogeneity could occur in particular through the feedback of inequality to innovation. For example, an increase 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 US Senate Committee on Appropriations which, among other things, allocates federal funds for research across United States. As a robustness test, we show in Section 6 this instrument can be combined with a second one which exploits knowledge spillovers across states.

5.1 Using the Appropriation Committee for an instrument

We instrument for innovation using the time-varying state composition of Appropriation Committees. 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).[32][33]

5.1.1 Institutional background

The Appropriation Committees of the Senate and of the House of Representatives are standing committees in charge of all discretionary spending legislation through appropriation bills. Discretionary funding are funding that are not required to be allocated to certain program by law (Social Security, unemployment compensation...). This discretionary budget is usually allocated 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.[34] However, the Appropriation Committees can also choose to add grants (or "earmarks") to the appropriation bill for specific projects, bypassing the usual peer-review competitive process (see Aghion et al., 2009; Cohen et al., 2011; Payne, 2003; Savage, 2000; and Feller, 2001).

A legislator who sits on an Appropriation Committee often pushes for earmarked grants in the state in which she represents, in order to increase her chances of reelection. As a result, federal research funding to universities in a state is influenced by the presence of a legislator from that state on the committee as shown by Payne (2003) and Savage (2000). 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." Evidence that research and research education are large beneficiaries from

[32]We have hand-collected data from various documents published by the Senate and compared congressmen' names with official biographical information to determine their appointment and termination dates.

[33]Pointing in the same direction, we find that the effect of (patented) innovation is stronger in states which specialize in sectors where patents are more important to protect innovation according to Cohen et al. (2000) (see Appendix B).

[34]Nevertheless, as mentioned by Payne (2003), a congressman can influence the use of the award by providing funding guidance to the agencies, which they typically comply with.

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): Universities rank at the top of the recipients list together with defense companies. We shall control for state-level highway and military expenditures in our IV regressions as detailed below.[35]

Based on these Appropriation Committee data, various instruments for innovation can be constructed. We follow the simplest approach by taking the number of senators (0, 1 or 2) who sit on the committee for each state and at each date.

5.1.2 Discussion

We now justify the use of Appropriation Committee membership as an instrument for innovation. We first argue that the composition of the Appropriation Committee is exogenous. Then, we explain that a nomination to the Appropriation Committee leads to an increase in earmarks received by a state. This boosts innovation in particular because it boosts university patenting which has positive spillovers on innovation, in general. We pay particular attention to the timing of each effect.

Exogeneity of the Appropriation Committee Membership A first concern with our instrument is that changes in the state composition of the Appropriation Committee could be related to growth or innovation performance in those states. However, as explained in Aghion et al. (2009), these changes are determined by events such as anticipated elections or, more unexpectedly, the death or retirement of current chairs or other members of these committees, followed by a complicated political process to find suitable candidates. This process in turn gives substantial weight to seniority considerations, while focusing on maintaining a fair political and geographical distribution of seats. Thus, in order to enter the Appropriation Committee, a legislator from any state i needs to wait for a seat to become vacant. This can happen only if an incumbent is not reelected (or resigns, or dies) which is not dependent on the economic situation in state i.

Relatedly, the composition of the appropriation committee might reflect the disproportionate attractiveness for innovation and wealthy individuals of states such as California and Massachusetts. Yet, less advanced states have been well represented: Alabama had one senator, Richard Shelby, on the Committee between 1995 and 2008 while California had no member until the early 1990s (see more details in Table C9 in Appendix C). 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 capita were Hawaii (Sen. Daniel Inouye of Hawaii was Chairman of the Senate Appropriation Committee at the time) and North Dakota. Other evidence reported by Savage (2000) shows that the top five states in terms

[35]See also Aghion et al. (2009), particularly Table 9 and Aghion et al. (2010), Figure 13.

of academic earmarks in total value (not per capita) were 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 receives almost the same amount as Hawaii. Cohen et al. (2011) report a table showing states receiving the largest amount of earmarks per capita on average from 1991 to 2008 are Hawaii, Alaska, West Virginia and Mississippi.[36]

A "zero-stage" regression of earmarks on Appropriation Committee composition. To show more systematically how Appropriation Committee membership affects the allocation of earmarks across the United States, we use hand-collected earmarks data gathered from "Citizen Against Government Waste" kindly provided by Cohen et al. (2011). These data associate a state with the "earmark" received during the year by that state. Then, we run a "zero-stage regression" of earmarks on Appropriation Committee composition. Formally, we run the following cross-state panel regression:

$$log(E_{i,t}) = \beta_0 + \beta_1 log(E_{i,t-1}) + \beta_2 Senator_{i,t} + X_{i,t}\gamma + B_i + B_t + \varepsilon_{i,t},$$

where t ranges from 1991 to 2008, $E_{i,t}$ denotes the earmarks per capita received by state i in year t, $Senator_{i,t}$ is the corresponding number of senators in the Appropriation Committee (0, 1 or 2); $X_{i,t}$ are our usual set of covariates; and B_t and B_i are year and state fixed effects.

We run the regression, first using total earmarks as our dependent (LHS) variable and then, using only earmarks which we considered to be "research earmarks" based on their title (for example $495,000 was appropriated to "Energy and Environmental Research Center at the University of North Dakota" in 1991). Since earmarks should promote innovation in a state, first through their impact on university research, we also run similar regressions using citations-weighted university patents per capita as the dependent variable, instead of earmarks.[37] Table 10 reports the results. They are consistent with the existing literature (Payne and Siow, 2003): Having one (or two) senator(s) in the committee is associated with increased earmarks and with more and better quality university patents to the corresponding state, compared to the US average in the same year.

Timing issue Our IV regression below assumes a three-year lag between the instrument and innovation in the first-stage regression. Is this a reasonable assumption? Consider first the example of Kentucky (KY) with the arrival of the current majority leader (Sen. Mitch

[36]We tested directly for reverse causality: is a state more likely to obtain an additional member in the Appropriation Committee when it becomes more unequal? We ran a Probit model where the left-hand side variable is a binary variable equal to 1 if a new senator from state i access the committee at t and the right-hand side variables include the number of senators from state i currently in the committee and the log of the top 1% income share at different lags. We did not find any significant effect of the top 1% share on the probability to access the committee.

[37]The list of university patents was provided by the USPTO and created by matching the name of the top 250 universities with the name of the patent assignee.

McConnell, KY) to the Appropriation Committee in January 1993.[38] Following McConnell's arrival, both earmarks and innovation immediately sharply increased. Thus, already in 1993 an earmark of more than four million dollars was allocated to the University of Kentucky Advanced Science & Technology Commercialization Center to further develop a business incubator housing new and emerging technology-based companies within the university. From our earmarks data, we see the share of total earmarks received by KY underwent a tenfold increase between 1992 and 1993.

McConnell's enrollment on the Appropriation Committee also induced a prompt and substantial increase in patents and citations from that state. To show this, we use a synthetic cohort approach as presented in Abadie et al. (2010). In short, we construct a "synthetic" (or "counterfactual") Kentucky, by pooling a set of other states selected by minimizing the distance in several characteristics between those states and Kentucky before 1993. Figures 6(a) and 6(b) show that the difference in the number of citations-weighted university patents per capita between the actual Kentucky and the "synthetic" one increases quickly and sharply after Senator McConnell's arrival on the Appropriation Committee in 1993; while if we consider all patents, the gap widens up three years later.

Of course this is just one example. We generalize these results by performing an event study exercise, the results of which are reported in Figures 7(a), 7(b) and 7(c). There, we restrict attention to states that experienced at least one increase in their representation on the Senate Appropriation Committee during our sample period.[39] We aggregate the average share of earmarks, citations-weighted university patents, and citations-weighted patents for these states (still indexed by their application year). For each of these states, "Year 0" corresponds to the year when its representation on the Appropriation Committee has increased. Figure 7(a) shows that a one-member increase in state representation on the Appropriation Committee translates almost immediately into a sharp increase in the amount of earmarks across states. This is consistent with the findings in Cohen et al. (2011). Figures 7(b) and 7(c) show that university innovation, as measured by a citation-weighted count of patents, also rises quickly after a one-member increase in state representation on the Appropriation Committee, and overall innovation increases three years after the change.[40]

Finally, our lag choice finds support in the literature. Payne and Siow (2003) find that

[38]Senator McConnell's accession to the committee followed the death of Senator Burdick in 1992. Even if he did not directly replace him, there were only four new senators in the committee in the next congress.

[39]The sample period depends on the measure we consider which in turns affects the number of states in our sample. To increase its size, we also include states that experienced more than one increase in their representation on the committee, in which case we only consider the first increase.

[40]Those figures also report the mean number of senators around the event—which may differ from 0 pre-event and 1 post-event as senators may leave the committee. Moreover, we find that the event has a significant effect on earmarks, in the sense that in Figure 7(a) the sum of the dummies at t+1, t+2, t+3 is significantly different from the sum of the dummies at t-1, t-2, t-3 at 5.7% level, the effect on university patents similarly defined is also significant at the 9.2% level, while the effect on patents defined as the sum of the dummies at t+3, t+4, t+5 relative to the sum of the dummies at t-1, t-2, t-3 is significant at 8.3%—these levels change to respectively 7.1, 7.3 and 8.8% if one adds our set of covariates to the exercise.

the appointment of an alumni to the House Appropriation Committee leads to an increase in the number of granted university patents after five years, which corresponds to an increase in patent applications after two years. Furthermore, we know from Jaffe (1989) that there are large contemporaneous spillovers from university research on corporate patenting. Daim et al. (2007) find a time lag between federal research funding in nanotechnology and patent grants of 5.5 years (which corresponds to a time lag of around 3 years for patent applications); Toole (2007) shows that in the pharmaceutical industry, the positive impact of public R&D on private R&D is the strongest after 1 year; and using shocks to defense R&D, Moretti et al. (2016) show that public R&D expenditures increase private R&D contemporaneously. Finally, Pakes and Schankerman (1984) and Hall et al. (1986) have found very little lag between private R&D and patent applications.

Controlling for other expenditures One final concern with our instrument is that not all earmarks fund research. For instance, (wealthy) owners of construction or military companies may capture part of the earmarked funds, given that many earmarks are dedicated to these sectors. In that case, the number of legislators sitting on the appropriation committee would be correlated with the top 1% income share, but for reasons having little to do with innovation. To deal with this possibility, we use yearly data from the Census Bureau on total federal allocation to states, by identifying the sources of state revenues. For each state we identify military expenditures and a particular type of infrastructure spending, namely highways, which is presented as a privileged source of earmarks by Aghion et al. (2009). We control for both in our regressions below.

5.2 Regression results

Table 11 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. Column 1 uses the number of patents as a measure of innovation, column 2 the number of citations in a 5-year window, column 3 the number of claims, column 4 the generality weighted patent count, and columns 5 and 6 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 (while innovation itself is lagged by 2 years in the main regression) in line with our above discussion. The resulting coefficient on innovation is always positive and significant, and, except for column 6, the F-statistics of the first stage regression is above 10, suggesting that our instrument is reasonably strong.

The results from the first stage regression and the reduced form regression are shown in columns 1 and 2 of Table 12. The coefficient in the reduced form regression suggests that the appointment of an additional senator to the Appropriation Committee increases top income inequality in that state by 1.6%. For the median state-year in terms of GDP (namely Arizona in year 1990 with a 103 billion dollars GDP), the top 1% share in fiscal income is 12.5%. Given that roughly half of the GDP ends up as taxable income, we predict a change in income of around 100 million dollars ($0.5 * 103 * 0.016 * 0.125$). As the average yearly earmark in a state with a senator on the Appropriation Committee is equal to roughly 150 million dollars, our regression results can be accounted for easily without assuming a large multiplier from public R&D to innovation income.[41]

5.3 Magnitude

We now consider the magnitude of the impact of innovation on top income inequality implied by Table 11: A 1% increase in the number of patents per capita increases the top 1% income share by 0.22% (column 1 in Table 11) and a 1% increase in the citation-based measures of innovation has a similar effect. This means for example that in California where the flow of patents per capita has been multiplied by 3.2 and the top 1% income share has been multiplied by 2.4 from 1980 to 2005, the increase in innovation can explain 29% of the increase in the top 1% income share over that period. On average across all states, the increase in innovation, as measured by the number of patents per capita, explains about 23% of the total increase in the top 1% income share over the period 1980-2005.

However, 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 is a better measure of innovation but is hard to compare over time; (ii) innovators from poor states may move to richer states, thereby not contributing to the top 1% share of their own state; (iii) an innovating firm may have some of its owners and top employees located in a different state from the inventor, so that all innovation rents may not accrue in the state of the patent. However, 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, which in turn would mean the increase in innovation could, in fact, explain less of the increase in the top 1% income share than what we infer from our regressions.[42]

Looking at cross state differences in a given year, we can compare the effect of innovation with that of other significant variables. Our IV regression suggests that if a state were to move from the first quartile in terms of the number of citations in 2005 to the fourth quartile, its top 1% income share would increase on average by 4.3 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 4.2-percentage-point increase in the top 1% income share.

[41] This is all the more true that Delaney (2011) finds that federal earmarks lead to higher state expenditures on research education (between 2 and 5 more dollars for each federal dollar).

[42] See the discussion in section 4.7. Although it is a debated topic, Kortum and Lerner (1999) argue that the sharp increase in the number of patents in the 1990s reflected a genuine increase in innovation and a shift towards more applied research instead of regulatory changes that would have made patenting easier.

5.4 Discussion

The following concerns could be raised by this regression. First, some of our control variables could be endogenous, conditional upon them, our instruments could be correlated with the unobservables in our model. Yet, the coefficient on innovation is still positive and significant when we only include state- and year-fixed effects in the regression.[43]

Second, the magnitude of the innovation coefficients in the IV regression is larger than in the OLS regressions. A potential reason lies in the relationship between innovation and competition. Our model shows that a higher level of mark-ups for non-innovative incumbents 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. More generally, 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 may result from an increase in lobbying or from special access to a new enlarged market. It will increase the firm's rents which in turn should contribute to increased inequality at the top. However, on this side of the inverted-U, it 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.[44]

5.5 Other IV results

Appendix C shows 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 the Gini coefficient (Table C10). Moreover, 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 the effect of lagged innovation is strongest after 2 years; and it becomes smaller and insignificant from five years (Table C11). These latter findings confirm those in the corresponding OLS Table 9, and again indicate that innovation has a temporary effect on top income inequality.

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

[44]Other mechanisms could explain the gap between the OLS and IV coefficients: Reducing inequality may increase innovation when potential innovators who are not in the top 1% face credit constraints which limit the scope of their innovative investments (see Benabou 1996, Aghion and Bolton 1997 and Aghion and Howitt 1998, Ch. 9). A high level of inequality could also lead to higher taxes which can harm innovation (Persson and Tabellini, 1994).

6 Robustness checks

6.1 Adding a second instrument

To add power to our instrumental variable estimation, 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. 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 (decrease θ_I or θ_E in the model). To build this predicted measure of innovation, we rely on Acemoglu et al. (2016) and integrate the idea that the spillover network can be very different at different lags between citing and cited patent. We thus compute a matrix of weights, where for each pair of states (i, j), and for each lag k between citing and cited patents (with k between 3 and 10 years),[45] $w_{i,j,k}$ denotes the relative weight of state j in the citations with lag k of patents issued in state i, aggregated over the period from 1976 to 1978.[46]

We then compute our instrument as follows: Let $m(i, j, t, k)$ denote 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 $innov(j, t-k)$ denote our measure of innovation in state j at time $t-k$, we posit:

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

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. We normalize by $Pop_{-i,t}$, as otherwise our measure of spillovers would mechanically put at a relative disadvantage a state which grows faster than the others (but doing so does not impact our results).

Reverse causality is not a big concern because the top 1% income share in one state is unlikely to cause innovations in other states.[47] Yet, one may worry that this instrument might capture regional or industry trends which affect both top income inequality and innovation. For example, a boom in a state may increase innovation both locally and in a neighboring state. Then, if there are many patent citations between these two states, our spillover

[45] Over 1976-2014, 67% of citations were made to patents filed less than 10 years before the citing patent.

[46] We observe all the patents which received citations from patents granted after 1976 even if the cited patents were granted before 1976 thanks to Hall et al. (2001).

[47] Reverse causality might arise from the same firm citing itself across different states, but removing citations from a firm to itself in different states when constructing the weights has no effect on the results.

variable would capture a positive correlation between innovation in the two states, even though this correlation would mainly reflect a common demand shock. In practice, this concern is mitigated both by the weak correlation between the knowledge spillover weights and geographical distance (below 15%) and by the (at least) 4-year time lag set between state innovation and the others states' innovation measures in the instrument. To proxy for such demand shocks, we build a control variable by computing a weighted average of other states' GDP per capita using as weights the $w(i, j, k)$'s averaged across lags k.

Similarly, consider now two states that are highly involved in, say, the computer sector. A demand shock in this sector would boost innovation and may increase the top 1% income share in both states, violating our exclusion restriction. The time lag once again mitigates this concern, but, to deal with such possibility, we build new weights based on the angular distance between states' industry composition in the manufacturing sector. These new weights are averaged over a three-year window. We use them to build another control variable which is the (re-)weighted sum of innovation in other states divided by $Pop_{-i,t}$.

Importantly, an overidentification test which uses the spillover and appropriation committee instruments does not reject the validity of the instruments: The p-value associated with the null hypothesis is always larger than 10%, which in turn reinforces the first instrument.[48] Table C12 in Appendix C presents the results from the IV regressions of top income inequality on the two instruments combined.[49] As in Table 11, the coefficients are always positive and significant (now at the 1% level). The coefficients are close to those of Table 11, which is all the more remarkable that the two instruments are uncorrelated once one controls for states and time fixed effects. The F-statistics for the two instruments combined is always above 10.

6.2 Additional robustness checks in the Appendix

In Appendix B.1 and B.2, we perform additional robustness checks. First, with regard to the financial sector: We build additional controls for wage compensations in the financial sector and for financial dependence of innovation in each state; we also exclude states which rely most heavily on the financial sector and we exclude financial innovations. Both our OLS and IV results are robust to all these additional tests.

Second, we perform similar robustness tests with respect to the oil industry: We remove the associated patents and control for the share of the oil extraction and mining sectors. We also check whether the most innovative sectors or export-oriented sectors drive our results, and we show that this is not the case. Additionally, we also remove innovators who have

[48] 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 the overidentification test would reject the null hypothesis.

[49] The results from the corresponding first stage and reduced form regressions, are shown in Table 12. In the Appendix C, Table C13, we show the results from the IV regressions using only the second instrument.

patented in several states and show that our results still hold.

Finally, we investigate the role of agglomeration effects, as these may drive both inequality and innovation. We build measures of urban density to show that controlling for such measures does not affect our results.

7 Reproducing our regression results from the model

We now calibrate the main parameters of the model and use our calibrated model to reproduce the regressions of the paper. Our goal is two-fold: Check whether our model and our empirical results can be consistent with each other for reasonable parameters; and assess whether the gap between the OLS and the IV coefficients can be rationalized. We focus on the case where there is no lobbying, i.e. $z = 0$, so that we are left with six parameters to calibrate: The mark-ups η_L and η_H, the R&D parameters θ_I and θ_E, L which is one-to-one related to the share of the population who obtains the monopoly rents (namely $1/(1+L)$) and the share ϕ of productive innovations among all incumbent innovations (technically ϕ is an equilibrium value, but since it is undetermined in equilibrium, we treat as a parameter). As explained in Section 2.3, we think of the number of innovations in the model as being proportional to the number of patents or citations-weighted patents in the data. We draw three among six moments from the data: The average top 1% share across US states between 1977 and 2011 ($M_1 = 0.13$), the ratio of citations to entrant over incumbent patents ($M_2 = 0.2$), and the elasticity of top income inequality with respect to innovation ($M_3 = 0.185$, the coefficient reported in Table 11, column 2).

We then fix the values of three moments from the literature: The average mark-up $M_4 = 1.2$ (according to Jaimovich and Floetotto, 2008, markups range from 1.2 to 1.4 in value added data and from 1.05 to 1.15 in gross output data); the share of employment in entering firms $M_5 = 0.03$ (in line with Garcia-Macia et al., 2016 who find an employment share for entrants of 15% when entrants are defined as firms with less than 5 years); and the growth rate of the economy $M_6 = 0.02$.

The model is fully identified and Appendix D details how each parameter is determined. In a nutshell, in the relevant case, the semi-elasticity, $M_1 * M_3 = \mu\left(\frac{1}{\eta_L} - \frac{1}{\eta_H}\right)$, increases both in the innovation rate μ and the innovation step η_H for a given η_L. Yet, for given harmonic average mark-ups, the entrant share of employment M_5 increases with the innovation rate μ but decreases with the innovation size η_H. Therefore $M_1 * M_3$ and M_5 together allow to separately identify μ and η_H. The low mark-up η_L is then adjusted to reproduce the average mark-up M_4. Given η_H, η_L and μ, the other parameters are identified through the top 1% share (for L), the innovation ratio and the innovation rate equations (for θ_I and θ_E) and the growth rate (for ϕ). Table 13 summarizes the moments that we target, their source, their value in the simulated data described below, and gives the value of the different parameters.

The model predicts a large gap between θ_I and θ_E because most innovations are done by incumbents. We find a low ϕ, so that a substantial fraction of incumbents' innovations are "defensive", which is consistent with a large role for innovations in explaining top income inequality, while at the same time measured GDP growth has been timid. With these parameters, the economy is in "case 2" of Section 2, where the top 1% includes all innovators and some incumbent entrepreneurs who failed at innovating. Moreover, with these parameters, an increase in η_L increases the top 1% share but reduces innovation.

We now use our calibrated model to reproduce the regressions of the paper. We consider that there are 51 states over a 28-year time span. In each state i, and each year t, the innovation costs for entrants and incumbents are $\theta_{E,i,t} = \theta_E \exp(\varepsilon_{\theta,i,t} + \varepsilon_{\theta,i})$ and $\theta_{I,s,t} = \theta_I \exp(\varepsilon_{\theta,i,t} + \varepsilon_{\theta,i})$, where the shocks $\varepsilon_{\theta,i,t}$ and $\varepsilon_{\theta,i}$ are respectively state-year and state-specific i.i.d shocks. The markup of non-innovators is given by $\eta_{L,i,t} = \eta_L + \varepsilon_{\eta,i,t} + \varepsilon_{\eta,i}$ where $\varepsilon_{\eta,i,t}$ and $\varepsilon_{\eta,i}$ are respectively state-year and state-specific i.i.d shocks. The parameters η_H and L are constant across states and years.

We compute for each year and state, the innovation rates and the top income shares $(\widehat{Top\_1\%\_share}_{i,t})$ as predicted by our model, and add "measurement errors" so that

$$Top\_1\%\_share_{i,t} = \widehat{Top\_1\%\_share}_{i,t} \times \exp(\varepsilon_{\delta,i} + \varepsilon_{\delta,t} + \varepsilon_{\delta,i,t}),$$

where $\varepsilon_{\delta,i}$, $\varepsilon_{\delta,t}$ and $\varepsilon_{\delta,i,t}$ are respectively state, year and state-year specific shocks. We consider that the number of citations in a state i at a year t is given by $Cit5_{i,t} = C\mu_{i,t} \exp(\varepsilon_{\mu,i,t})$, where $\mu_{i,t}$ is the number of innovations, C is a constant and $\varepsilon_{\mu,i,t}$ represent measurement errors. We then run the following regression:

$$\log Top\_1\%\_share_{i,t} = A + B_i + B_t + \beta_1 \log Cit5_{i,t} + \varepsilon_{i,t},$$

first in OLS and then in IV where we instrument $Cit5_{i,t}$ by $\varepsilon_{\theta,i,t} + \varepsilon_{\theta,i}$ (which corresponds to a shock to the innovation technology akin to our appropriation committee instrument).

We set the standard deviations of the different shocks to match second order moments in the data as explained in Appendix D. The OLS and IV coefficients, averaged over 500 draws on the simulated data, give a coefficient of 0.184 for the IV (close to the target coefficient 0.185 from column 2 of Table 11), and 0.051 for the OLS, close to the 0.049 figure reported in column 2 of Table 4.[50] Figure D1 in Appendix D plots the whole distribution of the IV coefficients and Table 13 shows the average value for the targeted moments in the simulated data. Therefore, we get a close mapping between the model's quantitative predictions and our empirical results.

Finally, this exercise makes it easier to understand the difference between the OLS and the IV coefficients in our regressions. The IV coefficient captures the effect of a shock to innovation costs and therefore the positive impact of innovation on top income inequality.

[50]The IV coefficient is quite stable as long as the standard errors are not too large. The OLS coefficient depends on how much variation there is in η_L at the state-year level relative to θ.

The OLS coefficient captures the overall correlation between innovation and top income inequality, which is less positive if only because the variation in η_L creates a negative relationship between innovation and top income inequality. Moreover, the noise on the citation variable further attenuates the OLS coefficient, though that effect is small (without it, the OLS coefficient would be on average equal to 0.070).

8 Innovation and social mobility

We now consider the relationship between innovation and social mobility. In the absence of state-level panel data on social mobility, and to avoid reducing the number of observations too much, we move from cross-state to cross-commuting zones (CZ) analysis. A CZ is a group of neighboring counties that share the same commuting pattern. There are 741 CZs covering the United States.

8.1 From cross-state to CZ-level analysis

We first check whether the effect of innovation on inequality measures at the CZ level is consistent with our cross-state panel findings. Since at the CZ level we do not have direct access to data on top income shares, we use the census data from 2000 and 2005-2011 to obtain individual earnings information. As the publicly available data are censored at the top, we follow Clemens et al. (2017) and assume a Pareto-shape distribution for large incomes, which allows us to "compute" top income shares for 726 CZs (details in Appendix E). We use the county of the inventor of each patent to associate it with a CZ (we obtained this information from the USPTO from 1998 onward).

Regressing top income inequality on innovation at the CZ level allows us to introduce both CZ fixed effects and state×year fixed effects, thereby absorbing any variation in innovation at the state-year level. To match our cross-state analysis as closely as possible, we add controls for the log of total income per capita, for the growth of total population, for the size of financial and local government sectors compared to the US average, and for unemployment.[51] Standard errors are clustered by state, and CZs are weighted by population to account for potential correlation across neighboring CZs and also to give more weight to urban areas.

We present the results in Table 14, where innovation is measured by the number of patents per capita (we run the regressions over the years 2000 and 2005-2011). We find a positive and significant coefficient for innovation, slightly smaller than in the state-level case.[52] Yet, there are several limits to this exercise: first, we rely on an estimate of top income shares based on

[51] We aggregate county level data on total income, financial and government sector size, unemployment and population from the BEA and the BLS to compute these variables.

[52] There are several CZ with 0 patent and interestingly, the coefficient capturing the extensive margin of innovation (as measured by the index taking the value 1 for CZ with no innovations) is negative and significant, so that CZ with no innovation exhibit less top income inequality.

censored data; second, the time interval is quite short;[53] third, since CZs are smaller than states, innovation rents are more likely than before to accrue to individuals who do not reside in the same geographical unit as the inventor; and fourth we cannot use our instrument.

8.2 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 around 30 years old, whereas the percentile P of parents income is calculated over the period 1996-2000, when the child was around 15 years old. The intensity of innovation in each CZ is measured by the number of citations per capita averaged over the period 1998-2008.

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 for CZ k. We cluster standard errors by state and weight CZ by population as before. Social mobility is based on the location of the parents, so that the data do not account for children who move to, and innovate in, a different location from that of their parents. Yet, this should bias our results downwards: If many individuals migrate out of a specific CZ to innovate in, say, San Francisco, this CZ will exhibit high social mobility, but low innovation.

Table 15 presents our results for this cross-section OLS regression, using the number of citations as a measure of innovation and the same set of control variables as in the previous subsection to which we add school expenditures per student and the employment share of the manufacturing sector (both from Chetty et al., 2014), and the average marginal tax rate. Columns 1 and 4 show the effect of innovation on upward mobility as measured by the child expected percentile in the income distribution at age 30 when parent income belongs to the 25th percentile ($AM25$). The effect 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 one of the two lowest quintiles, $P(1,5)$ and $P(2,5)$. The correlation between innovation and social mobility is more positive and significant for the lowest quintile than for the second lowest one. In fact, it becomes insignificant for the third and forth quintiles, and the coefficient in column 7, which measures

[53] In fact, when we measure innovation by the number of citations per capita, the panel is even shorter (it only includes years 2000 and 2005-2008), and the coefficient ceases to be significant.

social mobility as the probability to reach the highest quintile when parent belonged to any lower quintile, is positive but insignificant at the usual thresholds.

The correlation between innovation and social mobility is economically significant. Column 5 shows that moving from the median CZ to the 75^{th} percentile CZ in innovation intensity (which corresponds to an increase in the number of citations per capita by a factor of 2.5) is associated with an increase of 1.2 percentage points in social mobility at the mean level (namely from 9.6% to 10.8%)—where social mobility is measured by the probability of reaching the top quintile when parents belong to the bottom quintile.[54]

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.

8.3 Lobbying, entrant and incumbent innovation

Our model further suggests that the effect of innovation on social mobility should operate mainly through entrant innovation, and that entry barriers should dampen it. To test these predictions, we conduct the same regressions as in the previous section but separating entrant and incumbent innovations on the right hand side of the regression equation, where entrants and incumbents are defined as in the cross state case. Table 16 presents our results when we use the expected rank measure $AM25$ for social mobility (Table C14 in Appendix C gives the results with the probability of reaching a higher quintile). Column 1 regresses social mobility on entrant innovation (measured by the number of citations), column 2 on incumbent innovation and column 3 shows a horse race regression. Entrant innovation has a larger effect than incumbent innovation and in the horse race regression, only its effect is significant. This shows that the effect of innovation on social mobility is mostly associated with entrant innovation.

Next, we look at the role of lobbying. We construct lobbying intensity as in the cross-state case by building from industry shares at the county level. We are left with 662 CZs which we separate in two groups of equal size with high and low lobbying activities. Column 4 (respectively 5) of Table 16 repeats the horse race regression of column 3 for CZs above (respectively below) median in terms of lobbying activities. The effect of entrant innovation on social mobility is positive and significant only for CZs that have low lobbying intensity, while the effect of incumbent innovation is always insignificant. These results confirm the view that lobbying dampens the impact of innovation on social mobility by reducing entry.

[54] As quintiles are defined at the national level, in some CZs, the size of the top quintile is very small. This could be cause for concern, but we reproduced our regressions after having removed the CZs where the top quintile has a size below 10% or below 15% (excluding respectively 7 and 100 CZs), all our results remained consistent with the previous regressions.

9 Conclusion

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

Our approach was 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.[55]

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

Second, our calibration results suggest that our simple model, once enriched to better account for firms' heterogeneity, could be used as a building block toward a full quantitative model of innovation, firm size distribution and top income inequality. Such a model would be useful to assess the contribution of innovation in the rise of market power (De Loecker and Eeckhout, 2017), and also to assess the impact of tax policy, innovation policy (R&D subsidies, patent policy) or competition and entry policy on innovation-led growth and top income inequality.

[55] See Aghion et al. (2018) for such a study using Finnish individual data over the period 1990-2000. See also Toivanen and Väänänen (2012) and Bell et al. (2017) for studies based on individual US data.

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Figures

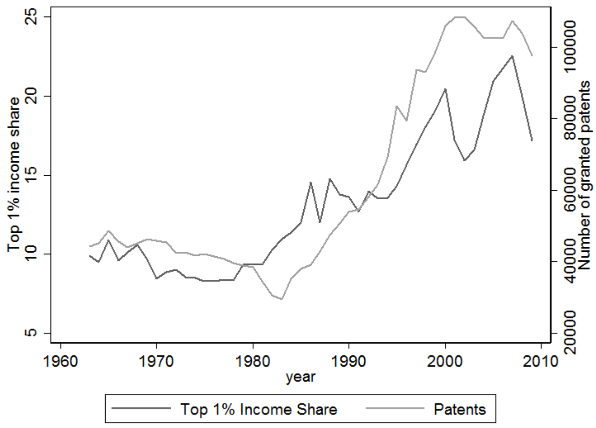


Figure 1: Innovation and Top 1% income share in the US. 1963-2010

Notes: This figure plots the number of granted patents distributed by their year of application against the top 1% income share for the USA as a whole. Observations span the years 1963-2009. Top 1% income shares come from Frank (2009) and patent data come from the USPTO.

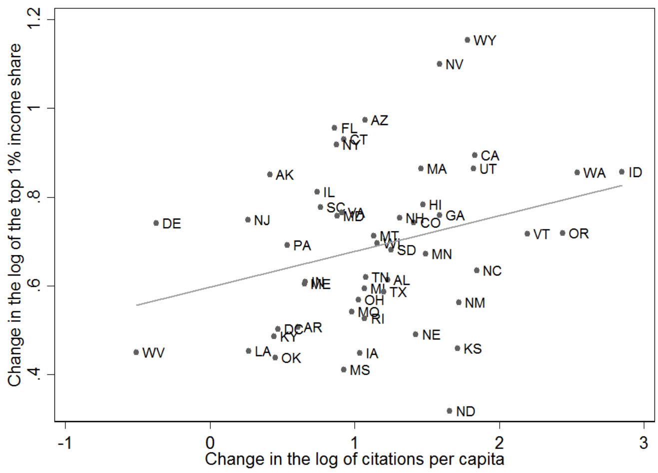


Figure 2: Evolution of innovation and inequality 1980-2005

Notes: 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.

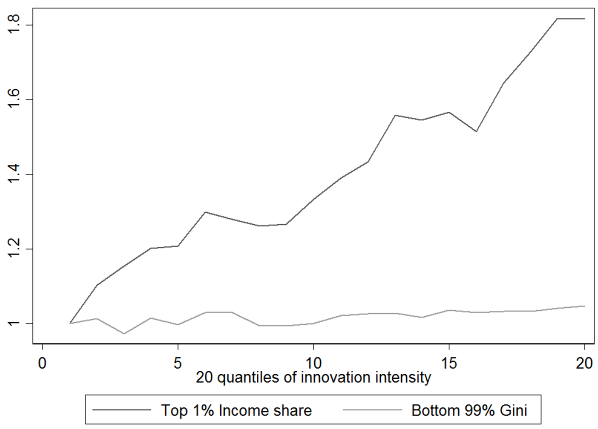


Figure 3: Top 1% income share and Gini coefficient against innovation

Notes: This figure plots the average top-1% income share and the bottom 99% Gini index as a function of their corresponding innovation quantile measured from the number of citations per capita. The bottom 99% Gini is the Gini coefficient when the top-1% of the income distribution is removed. Innovation quantiles are computed using the US state-year pairs from 1976 to 2009. Each series is normalized by its value in the lowest innovation quantiles.

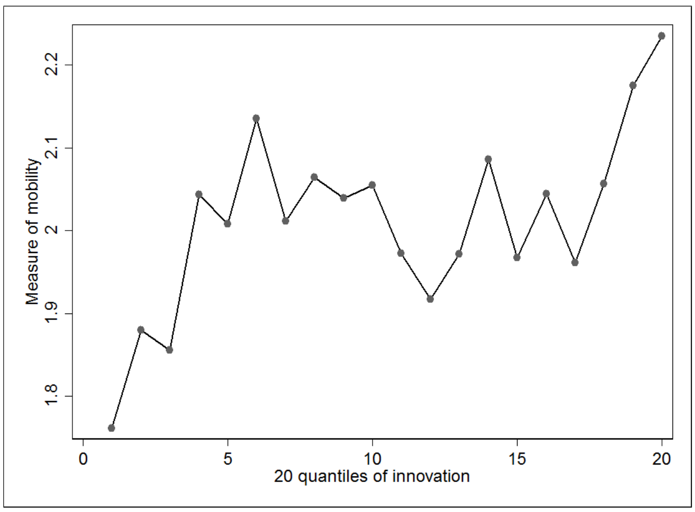


Figure 4: Innovation and social mobility

Notes: This figures plots the percentile in the number of patents 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) and is taken in log. Observations are computed at the Commuting Zones level (677 observations). The number of patents is averaged from 2005 to 2009.

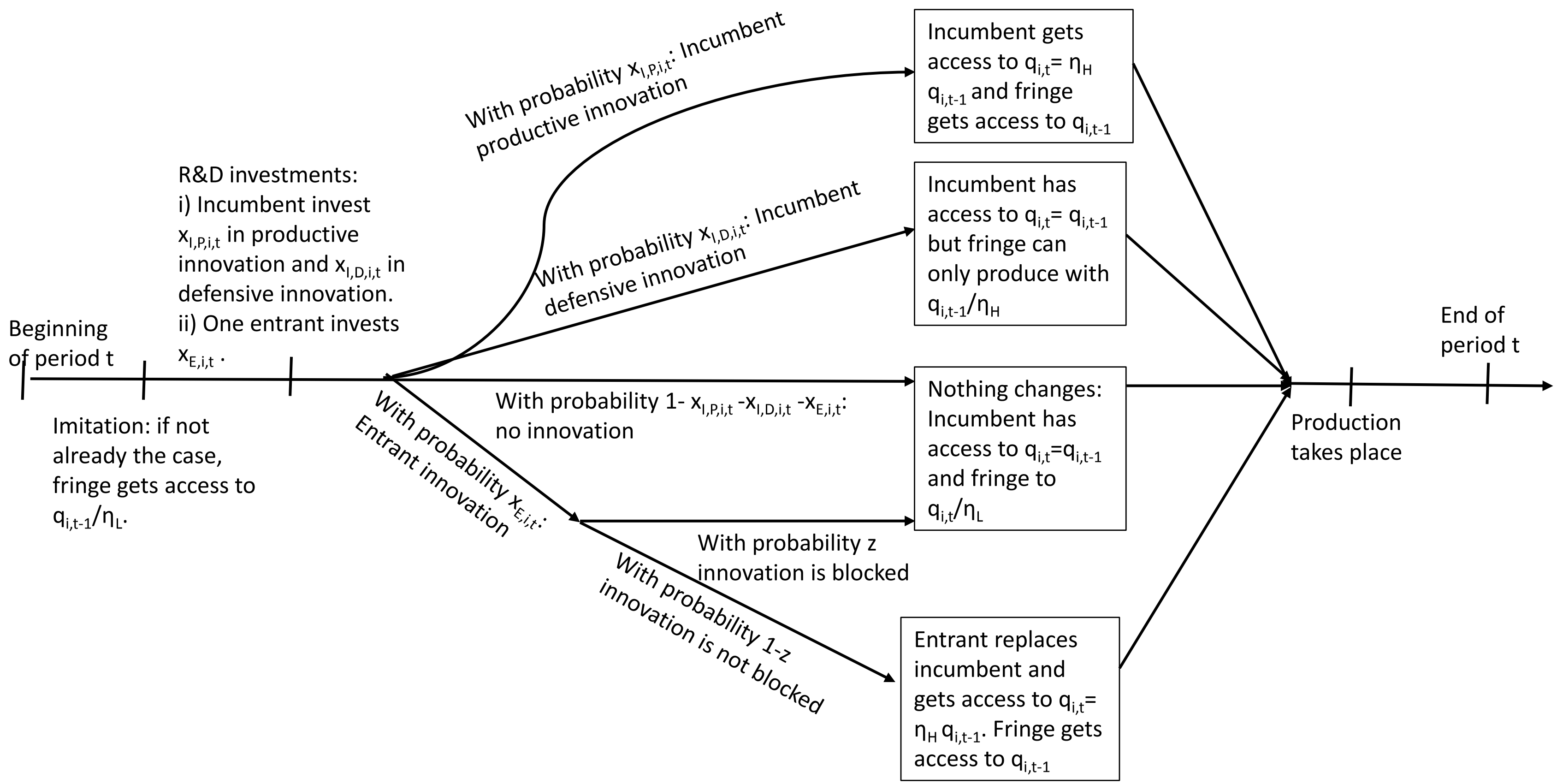
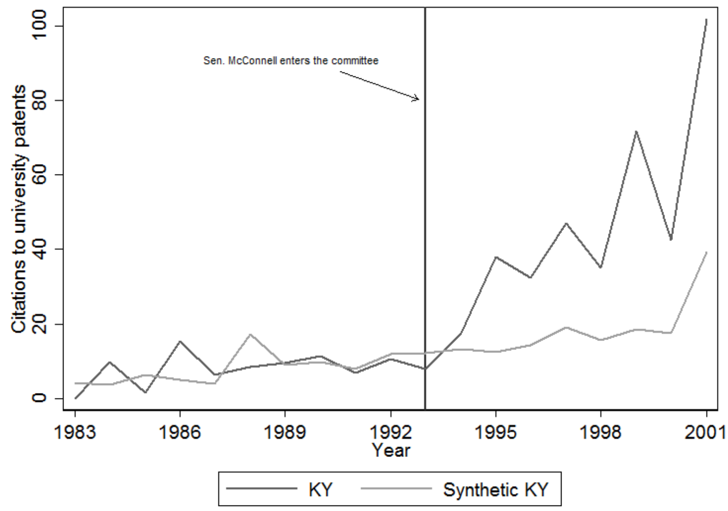


Figure 5: Timeline of events in theoretical model

Notes: This figure shows the timing of events as described in the theoretical model in Section 2.

(a) University patents



(b) All citations

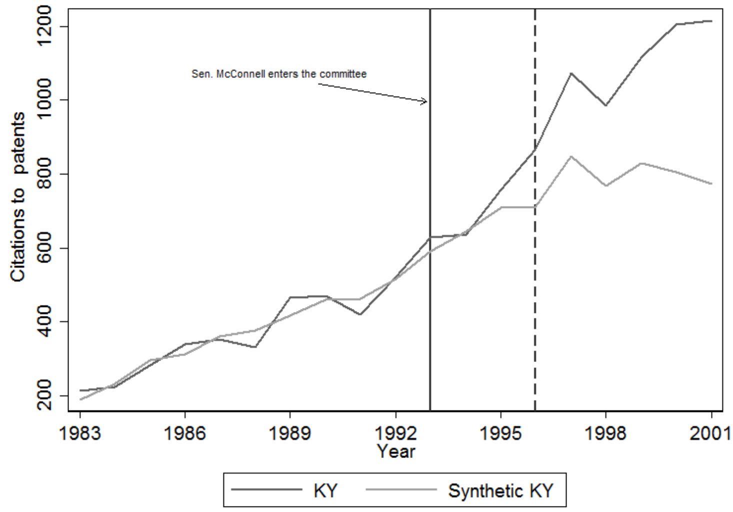
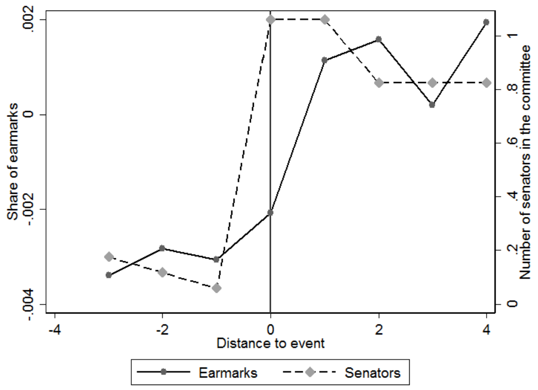


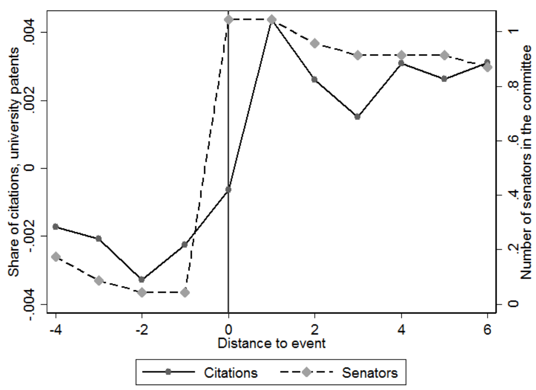
Figure 6: Synthetic cohort analysis

Notes: This figure plots the number of citations received within a 5-year window by all patents (left-hand side figure) and restricting to university patents (right-hand side figure) for the Kentucky and a synthetic Kentucky built by minimizing the distance in terms of size of financial sector, size of public sector, size of the manufacturing sector, GDP growth rate and user cost of R&D taken from Moretti and Wilson (2017). Minimization has been conducted from 1983 to 1991. Treatment year, corresponding to the arrival of Senator McConnell in the appropriation committee is 1993. The list of university patents has been received directly from the USPTO.

(a) Earmarks



(b) Citations to university patents



(c) Citations to all patents

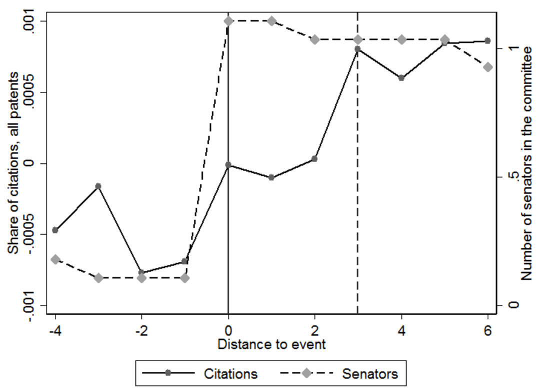


Figure 7: Event studies

Notes: This figure plots the average share of earmarks, citations to university patents and all citations at different times around the appointment of a senator in the appropriation committee. All measures have been residualized on a state-specific time trend. Sample is restricted to years 1991-2008 for the top-left panel, 1980-2006 for the top-right panel and 1976-2006 for the bottom panel, and to states which experienced one, and only one, positive change in their representation on the committee. The vertical solid line corresponds to the arrival of a new senator in the committee, the dashed line corresponds to 3 years after this event. The list of university patents has been received directly from the USPTO. The list of earmarks has been received from Cohen et al. (2011).

Tables

Table 1: Variable description and notation

Variable names	Description
	Measures of inequality
Top i%	Share of income own by the top i% (i being equal to 1, 5, 10, 0.01, 0.1...) of the income distribution.
Avgtop	Average income share for the percentiles 10 to 2 in the income distribution.
Gini	Gini index of inequality. The Gini index measures the dispersion of the income distribution.
G99	Gini index restricted to the bottom 99% of income distribution.
Atkinson	Atkinson index of inequality with an inequality aversion parameter of 0.5. The Atkinson index is a measure of the gain in terms of utility that would be gained if a total redistribution of the income distribution were to be done.
	Measures of innovation
Patent	Number of patents granted by the USPTO per capita.
Cit5	Total number of citations received no longer than 5 years after applications per capita.
Claims	Total number of claims associated with patents per capita.
Generality	Total number of patents weighted by the generality index per capita.
Top5	Number of patents in the top 5% most cited per capita.
Top1	Number of patents in the top 1% most cited per capita.
	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 GDP accounted for by the financial sectors divided by the same share at the country level.
Unemployment	Unemployment rate. Between 0 and 1.
Gvtsize	Share of GDP accounted for by the government sectors divided by the same share at the country level.
TaxK	State maximal marginal tax rate for realized capital gains.
TaxL	State maximal marginal tax rate for labor income.
	Additional control variables at the CZ level
Tax	Total tax revenue per capita divided by mean household income per capita for working age adults.
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 2: Descriptive statistics by measures of innovation and for the 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	140	71	113	186	27	501
Cit5	146	64	113	209	21	588
Claims	1,347	659	1,041	2,004	222	5,390
Generality	27	12	20	36	3	130
Top5	8	3	5	12	0	41
Top1	3	1	2	4	0	13
2005	Mean	p25	p50	p75	Min	Max
Top 1%	19.07	16.12	17.65	20.77	12.47	33.3
Patents	296	131	230	403	47	904
Cit5	508	161	373	618	44	1,689
Claims	4,567	1,915	3,045	5,599	630	24,964
Generality	104	50	82	152	19	366
Top5	10	2	7	12	0	36
Top1	2	1	1	3	0	9

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 1). All innovation measures are taken per million of inhabitants.

Table 3: Mean and Standard Deviation of the main variables

	Mean	Std dev
Top 1% (log)	2.591	0.267
Patent (log)	5.105	0.764
Cit5 (log)	5.678	1.074
Gdppc (log)	10.49	0.319
Popgrowth	0.010	0.011
Finance	0.920	0.237
Government	1.033	0.273
Unemployment	5.940	2.051
TaxK	4.386	2.948
TaxL	5.297	3.267

Notes: Mean value and standard deviation for the main variables calculated over the period 1980-2005 (relevant variables are defined in Table 1). GDP per capita is calculated in $ per capita and the innovation measures are taken per million of inhabitants.

Table 4: Top 1% income share and innovation

Dependent variable	Log of Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.031***	0.049***	0.017*	0.024**	0.026***	0.020***
	(0.011)	(0.009)	(0.009)	(0.010)	(0.005)	(0.004)
Gdppc	0.089**	0.063	0.096**	0.093**	0.074*	0.087**
	(0.043)	(0.044)	(0.045)	(0.043)	(0.043)	(0.043)
Popgrowth	0.943	1.089	0.943	0.934	0.990	1.074
	(0.654)	(0.700)	(0.651)	(0.647)	(0.690)	(0.685)
Finance	0.080**	0.109***	0.072**	0.078**	0.098***	0.094***
	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)	(0.035)
Government	-0.018	-0.019*	-0.018	-0.018	-0.018	-0.016
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment	-0.006**	-0.006*	-0.005*	-0.006*	-0.006*	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
TaxK	-0.038***	-0.039***	-0.038***	-0.038***	-0.038***	-0.037***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
TaxL	0.017***	0.014**	0.017***	0.018***	0.013**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
R^2	0.889	0.896	0.889	0.889	0.895	0.895
Observations	1734	1581	1734	1734	1581	1581

Notes: Variable description is given in Table 1. Innovation is taken in log and lagged by two years. The dependent variable is the log of the top 1% income share. Panel data OLS regressions with state and year fixed effects. Time span for innovation: 1976-2009 (columns 1, 3 and 4) and 1976-2006 (columns 2, 5 and 6). Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** 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%	Top 10 %	Avgtop	Overall Gini	G99	Atkinson
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Cit5	Cit5	Cit5	Cit5	Cit5	Cit5
Innovation	0.049***	0.022***	0.007	-0.001	-0.010**	0.017***
	(0.009)	(0.006)	(0.005)	(0.003)	(0.005)	(0.004)
Gdppc	0.063	0.032	0.002	0.004	-0.021	0.131***
	(0.044)	(0.028)	(0.030)	(0.024)	(0.028)	(0.029)
Popgrowth	1.089	0.553	0.265	-0.382**	-0.553**	0.402
	(0.700)	(0.424)	(0.381)	(0.184)	(0.240)	(0.276)
Finance	0.109***	0.066***	0.021	0.011	-0.018	0.037**
	(0.036)	(0.020)	(0.017)	(0.012)	(0.015)	(0.018)
Government	-0.019*	-0.005	0.013*	-0.004	0.001	-0.029***
	(0.011)	(0.007)	(0.007)	(0.004)	(0.005)	(0.006)
Unemployment	-0.006*	-0.001	0.002	-0.000	0.002	-0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
TaxK	-0.039***	-0.018***	-0.002	-0.007***	-0.001	-0.018***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
TaxL	0.014**	0.007*	-0.001	0.004**	0.001	0.011***
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
R^2	0.896	0.818	0.420	0.865	0.730	0.942
Observations	1581	1581	1581	1581	1581	1581

Notes: Variable description is given in Table 1. Innovation is taken in log and lagged by two years. Panel data OLS regressions with state and year fixed effects. Time span for innovation: 1976-2006. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 6: 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)**
Measure of innovation	Cit5	Cit5	Cit5	Cit5	Cit5	Cit5
Innovation	0.022***	0.026***	0.049***	0.060***	0.076***	0.094***
	(0.006)	(0.006)	(0.009)	(0.010)	(0.013)	(0.019)
Gdppc	0.032	0.050	0.063	0.055	0.060	0.046
	(0.028)	(0.036)	(0.044)	(0.055)	(0.068)	(0.095)
Popgrowth	0.553	0.618	1.089	1.595*	2.289**	3.307**
	(0.424)	(0.466)	(0.700)	(0.829)	(1.120)	(1.567)
Finance	0.066***	0.063**	0.109***	0.124***	0.079	0.021
	(0.020)	(0.025)	(0.036)	(0.046)	(0.072)	(0.106)
Government	-0.005	-0.009	-0.019*	-0.020*	-0.014	0.014
	(0.007)	(0.008)	(0.011)	(0.011)	(0.013)	(0.018)
Unemployment	-0.001	-0.005**	-0.006*	-0.008**	-0.010*	-0.014**
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)
TaxK	-0.018***	-0.023***	-0.039***	-0.047***	-0.061***	-0.084***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.009)
TaxL	0.007*	0.012***	0.014**	0.018***	0.024***	0.031**
	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.012)
R^2	0.818	0.877	0.896	0.893	0.891	0.864
Observations	1581	1581	1581	1581	1581	1581

Notes: Variable description is given in Table 1. Innovation is taken in log and lagged by two years. The dependent variables are taken in log. Panel data OLS regressions with state and year fixed effects. Time span for innovation: 1976-2006. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 7: Top 1% income share and innovation by entrants and incumbents

Dependent variable	Log of Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Patents	Patents	Cit5	Cit5	Cit5
Innovation						
by entrants	0.015*		0.011	0.017***		0.014**
	(0.008)		(0.008)	(0.006)		(0.006)
by incumbents		0.018***	0.016**		0.025***	0.022***
		(0.007)	(0.007)		(0.006)	(0.006)
Gdppc	0.110**	0.082	0.093*	0.080	0.054	0.056
	(0.052)	(0.055)	(0.053)	(0.059)	(0.060)	(0.058)
popgrowth	2.044***	1.997***	2.106***	2.287***	2.133***	2.208***
	(0.748)	(0.749)	(0.755)	(0.833)	(0.816)	(0.832)
Finance	0.097***	0.112***	0.107***	0.110***	0.135***	0.131***
	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)
Government	-0.021	-0.024	-0.019	-0.023	-0.027	-0.020
	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Unemployment	-0.002	-0.003	-0.003	-0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
TaxK	-0.038***	-0.038***	-0.038***	-0.038***	-0.039***	-0.039***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
TaxL	0.025***	0.026***	0.027***	0.022***	0.023***	0.024***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
R^2	0.852	0.851	0.852	0.859	0.860	0.862
Observations	1530	1530	1530	1377	1377	1377

Notes: Variable description is given in Table 1. Innovation by entrants is a count of innovation that restricts to patents whose assignee first patented less than 3 years ago. Other patents enter in the count of Innovation by incumbents. Both these measures of innovation are taken in log and lagged by two years. Panel data OLS regressions with state and year fixed effects. Time span for innovation: 1980-2009 (columns 1 to 3) and 1980-2006 (columns 4 to 6). Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 8: Top 1% income share, innovation and the role of lobbying intensity

Dependent variable	Log of Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Patents	Cit5	Claims
Innovation						
by entrants	0.905***	0.527**	0.837***			
	(0.000)	(0.014)	(0.000)			
by incumbents				0.246	0.196	0.307*
				(0.172)	(0.312)	(0.091)
Lobbying×Innovation						
by entrants	-0.051***	-0.030**	-0.048***			
	(0.000)	(0.015)	(0.000)			
by incumbents				-0.016	-0.011	-0.019*
				(0.132)	(0.320)	(0.073)
Lobbying	-0.305	-0.151	-0.095	0.053	-0.100	0.079
	(0.245)	(0.468)	(0.683)	(0.813)	(0.631)	(0.707)
Gdppc	0.107	0.014	0.105	0.095	-0.013	0.091
	(0.384)	(0.924)	(0.397)	(0.473)	(0.929)	(0.482)
Popgrowth	0.401	-0.146	0.379	0.640	0.150	0.622
	(0.738)	(0.897)	(0.754)	(0.613)	(0.902)	(0.622)
Finance	-0.021	-0.062	-0.027	-0.019	-0.057	-0.018
	(0.726)	(0.326)	(0.663)	(0.749)	(0.348)	(0.754)
Government	-0.107*	-0.189***	-0.108*	-0.117*	-0.221***	-0.115*
	(0.085)	(0.006)	(0.086)	(0.066)	(0.001)	(0.064)
Unemployment	-0.010**	-0.022***	-0.010**	-0.011**	-0.023***	-0.011**
	(0.026)	(0.000)	(0.023)	(0.016)	(0.000)	(0.015)
TaxK	-0.013**	-0.014**	-0.012**	-0.013**	-0.015***	-0.013**
	(0.025)	(0.012)	(0.028)	(0.023)	(0.010)	(0.022)
TaxL	-0.002	0.003	-0.003	-0.002	0.003	-0.002
	(0.840)	(0.815)	(0.815)	(0.844)	(0.811)	(0.884)
R^2	0.684	0.739	0.685	0.678	0.734	0.677
Observations	714	561	714	714	561	714

Notes: Lobbying is measured as explained in subsection 4.4. Other variable description is given in Table 1. Innovation is taken in log and lagged by two years. Columns 1 to 3 consider entrant innovation whether columns 4 to 6 consider incumbent innovations. The dependent variable is taken in log. Panel data OLS regressions with state and year fixed effects. Time span for innovation: 1996-2009 (columns 1, 3, 4 and 6) and 1996-2005 (columns 2 and 5). Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 9: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Log of Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Cit5	Cit5	Cit5	Cit5	Cit5	Cit5
Lag of innovation	2 years	3 years	4 years	5 years	6 years	All lags
Innovation at $t-2$	0.044***					0.029*
	(0.010)					(0.017)
Innovation at $t-3$		0.040***				0.016
		(0.009)				(0.015)
Innovation at $t-4$			0.039***			0.022
			(0.009)			(0.016)
Innovation at $t-5$				0.030***		-0.003
				(0.009)		(0.014)
Innovation at $t-6$					0.022**	-0.019
					(0.010)	(0.016)
Gdppc	0.034	0.035	0.033	0.045	0.057	0.027
	(0.062)	(0.062)	(0.062)	(0.062)	(0.061)	(0.063)
Popgrowth	2.210***	2.267***	2.307***	2.281***	2.296***	2.204***
	(0.839)	(0.838)	(0.827)	(0.829)	(0.828)	(0.846)
Finance	0.139***	0.134***	0.133***	0.126***	0.121***	0.141***
	(0.034)	(0.033)	(0.033)	(0.033)	(0.034)	(0.035)
Government	-0.025	-0.027	-0.028	-0.029	-0.030	-0.024
	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)
Unemployment	-0.003	-0.003	-0.003	-0.002	-0.002	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
TaxK	-0.039***	-0.039***	-0.038***	-0.039***	-0.038***	-0.039***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
TaxL	0.022***	0.022***	0.022***	0.022***	0.021***	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.860	0.860	0.860	0.859	0.858	0.861
Observations	1377	1377	1377	1377	1377	1377

Notes: Variable description is given in Table 1. Innovation is taken in log. The lag between the dependent variable and the innovation measures ranges from 2 years to 6 years. Panel data OLS regressions with state and year fixed effects. Time span for innovation: 1980-2006. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 10: SENATE APPROPRIATION COMMITTEE COMPOSITION AND EARMARKS

Dependent variable	Log of earmarks				Cit5 univ	
	All earmarks		Research earmarks			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SenateMember	0.401***	0.331***	0.330***	0.310***	0.096**	0.089**
	(0.076)	(0.074)	(0.113)	(0.103)	(0.048)	(0.037)
Gdppc	-1.003	-0.327	-4.092***	-3.182***	0.746**	0.448
	(0.708)	(0.703)	(1.002)	(0.988)	(0.367)	(0.283)
Ppgrowth	-0.805	-2.825	2.623	1.949	-4.337	-2.851
	(5.519)	(5.111)	(8.062)	(7.659)	(3.411)	(2.726)
Finance	0.651	0.213	0.292	0.290	-1.018***	-0.606***
	(0.479)	(0.422)	(0.601)	(0.524)	(0.253)	(0.203)
Government	-0.144	0.228	0.333	0.059	0.169	0.134
	(0.518)	(0.522)	(0.532)	(0.559)	(0.103)	(0.095)
Unemployment	-0.016	-0.016	-0.101*	-0.050	-0.052**	-0.030
	(0.037)	(0.031)	(0.055)	(0.054)	(0.022)	(0.018)
TaxK	0.050	0.085*	0.052	0.038	-0.025	-0.013
	(0.047)	(0.047)	(0.062)	(0.056)	(0.030)	(0.024)
TaxL	-0.062	-0.174*	-0.287**	-0.127	0.133***	0.083**
	(0.089)	(0.101)	(0.142)	(0.131)	(0.046)	(0.036)
$Y_{i,t-1}$		0.160***		0.201***		0.338***
		(0.039)		(0.040)		(0.031)
R^2	0.636	0.637	0.426	0.449	0.588	0.637
Observations	918	867	918	867	1428	1428

Notes: The dependent variable in columns 1 to 4 is the log of total earmarks received per capita in the state and comes from Cohen et al. (2011). Research earmarks have been selected based on the title on the appropriation bill. Columns 5 and 6 used the citations received within a 5-year window to patent assigned to universities. Panel data OLS regressions with state and year fixed effects. $Y_{i,t-1}$ denotes the lagged value of the dependent variable. Other variables description is given in Table 1. Autocorrelation and heteroskedasticity robust standard errors computed using the Newey-West variance estimator are reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 11: Regression of innovation on top 1% income share using instrument based on Appropriation Committee composition in the Senate

Dependent variable	Log of Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Measure of innovation	Patents	Cit5	Claims	Generality	Top5	Top1
Innovation	0.220**	0.185**	0.201**	0.233**	0.143**	0.153**
	(0.102)	(0.078)	(0.100)	(0.113)	(0.066)	(0.074)
Gdppc	-0.103	-0.079	-0.151	-0.138	-0.104	-0.079
	(0.109)	(0.093)	(0.138)	(0.130)	(0.107)	(0.102)
popgrowth	1.960**	1.663*	2.348**	2.101**	1.534*	1.886**
	(0.937)	(0.969)	(1.034)	(0.949)	(0.932)	(0.961)
Finance	0.179***	0.213***	0.175***	0.198***	0.209***	0.232***
	(0.061)	(0.068)	(0.066)	(0.073)	(0.073)	(0.086)
Government	-0.097***	-0.078***	-0.099***	-0.101***	-0.037	-0.014
	(0.024)	(0.024)	(0.025)	(0.027)	(0.030)	(0.042)
Unemployment	-0.012**	-0.012**	-0.013**	-0.014**	-0.012**	-0.007
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
TaxK	-0.040***	-0.039***	-0.041***	-0.043***	-0.039***	-0.036***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
TaxL	0.022***	0.016**	0.025***	0.027***	0.014**	0.014*
	(0.008)	(0.007)	(0.009)	(0.010)	(0.007)	(0.008)
Highways	0.398	0.511	0.454	0.427	0.417	0.669
	(0.448)	(0.464)	(0.486)	(0.489)	(0.452)	(0.541)
Military	-0.002	-0.004	-0.003	-0.002	-0.008	-0.004
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
R^2	0.866	0.874	0.851	0.846	0.844	0.812
F-stat on the excluded instruments	15.5	14.2	12.2	10.4	10.7	7.6
Observations	1700	1550	1700	1700	1550	1550

Notes: Variable description is given in Table 1. Innovation is taken in log and lagged by two years. Panel data IV 2SLS regressions with state and year fixed effects. Innovation is instrumented by the number of senators that sit on the appropriation committee. The lag between the instrument and the endogenous variable is set to 3 years. Time span for innovation: 1976-2009 for columns 1, 3 and 4 and 1976-2006 for columns 2, 5 and 6. DC is removed from the sample because it has no senators. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 12: 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	0.089***	0.016**			0.074***	0.017***
	(0.023)	(0.006)			(0.023)	(0.007)
Spillover			6.943***	1.047***	6.774***	1.027***
			(1.062)	(0.223)	(1.068)	(0.225)
Gdppc	1.039***	0.115**	1.021***	0.088	1.046***	0.094
	(0.163)	(0.046)	(0.192)	(0.062)	(0.175)	(0.066)
Popgrowth	-2.692	1.231*	-0.668	2.880***	0.752	2.775***
	(2.703)	(0.706)	(2.850)	(0.917)	(2.611)	(0.916)
Finance	-0.801***	0.072**	-0.672***	0.123***	-0.677***	0.118***
	(0.129)	(0.033)	(0.142)	(0.033)	(0.134)	(0.034)
Government	-0.037	-0.082***	-0.013	-0.092***	0.010	-0.087***
	(0.065)	(0.024)	(0.084)	(0.028)	(0.079)	(0.028)
Unemployment	0.045***	-0.004	0.065***	-0.001	0.067***	-0.001
	(0.012)	(0.003)	(0.012)	(0.004)	(0.011)	(0.004)
TaxK	0.016	-0.033***	0.009	-0.032***	0.005	-0.033***
	(0.014)	(0.004)	(0.016)	(0.005)	(0.016)	(0.005)
TaxL	-0.023**	0.005*	-0.020*	0.010***	-0.014	0.010***
	(0.010)	(0.003)	(0.011)	(0.004)	(0.011)	(0.004)
Highways	-2.546*	0.012			-5.081***	0.768**
	(1.457)	(0.317)			(1.344)	(0.375)
Military	0.003	-0.004			-0.029	-0.003
	(0.020)	(0.007)			(0.025)	(0.009)
R^2	0.845	0.927	0.855	0.869	0.861	0.871
Observations	1550	1550	1350	1350	1350	1350

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 instrument and columns 5 and 6 use all instruments. The lags between the dependent variable and the instruments are set to match the corresponding second 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. Two additional controls for demand shocks are included, as explained in subsection 6.1, in columns 3 to 6. Time Span: 1976-2006 for columns 1 and 2 and 1981-2006 for columns 3 to 6. Variable description is given in Table 1. Panel data OLS regressions with state and year fixed effects. Innovation as well as the top 1% income share are taken in log. Autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 13: Simulation results

Moments			Parameters
Definition and source	Target	Simulations	
M_1 Average top 1% share (own data)	0.130	0.13	$\eta_L = 1.16$
M_2 Ratio of entrant to incumbent citations (own data)	0.2	0.25	$\eta_H = 1.35$
M_3 Elasticity of top 1% w.r.t innovation (Garcia-Macia et al., 2016)	0.185	0.184	$\theta_I = 0.7$
M_4 Average mark-up (Jaimovich and Floetotto, 2008)	1.2	1.20	$\theta_E = 7.3$
M_5 Entrant share of employment (own data)	0.03	0.031	$L = 74.8$
M_6 Growth rate	0.02	0.020	$\phi = 0.196$

Notes: Definition and value of the targeted moments, average value for the targeted moments in 500 draws of simulated data and parameters

Table 14: Top 1% income share and innovation - CZ level panel

Dependent variable	Log of Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of innovation	Patents	Patents	Patents	Patents	Patents
Innovation	0.021*	0.019*	0.019*	0.019*	0.018*
	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)
Gdppc		-0.352	-0.359	-0.540**	-0.596**
		(0.217)	(0.217)	(0.260)	(0.288)
Popgrowth			0.333	0.277	0.011
			(0.561)	(0.508)	(0.428)
Finance				0.002	0.007
				(0.086)	(0.088)
Government				-0.187**	-0.166**
				(0.088)	(0.078)
Unemployment					-1.814
					(1.452)
R^2	0.816	0.818	0.812	0.813	0.814
Observations	5599	5599	5571	5570	5570

Notes: Variable description is given in Table 1. A dummy equal to one if the CZ belongs to an urban area is included but not reported. Panel fixed effect regression with CZs weighted by population and state×year dummies. Time span for innovation: 1998 and 2003-2009. Regressions also include a dummy for being an urban CZ. Heteroskedasticity robust standard errors clustered at the state level are reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 15: 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)**
Measure of innovation	Cit5	Cit5	Cit5	Cit5	Cit5	Cit5	Cit5
Innovation	0.015	0.076*	0.028	0.023**	0.112**	0.053**	0.012
	(0.010)	(0.042)	(0.025)	(0.010)	(0.042)	(0.025)	(0.017)
Gdppc	0.025	0.416*	0.158	-0.074	0.007	-0.144	-0.051
	(0.054)	(0.235)	(0.136)	(0.062)	(0.255)	(0.148)	(0.106)
Popgrowth	-1.156	-1.322	-5.852**	-1.944**	-4.976	-8.218***	-7.210***
	(0.850)	(3.667)	(2.539)	(0.838)	(3.628)	(2.288)	(1.600)
Government	0.047	0.263*	0.119	0.038	0.227	0.088	0.051
	(0.032)	(0.133)	(0.090)	(0.033)	(0.138)	(0.093)	(0.066)
Finance	0.032	0.035	0.093*	0.016	-0.023	0.045	0.046
	(0.021)	(0.083)	(0.054)	(0.019)	(0.073)	(0.054)	(0.039)
Unemployment	-0.025	0.720	-0.202	-0.201	-0.026	-0.740	-0.723*
	(0.212)	(0.908)	(0.604)	(0.211)	(0.872)	(0.550)	(0.398)
Tax	0.000	0.001	0.001	-0.001	-0.004	-0.003	-0.001
	(0.001)	(0.006)	(0.004)	(0.002)	(0.006)	(0.005)	(0.004)
School Expenditure				0.008	0.027	0.024	0.016
				(0.009)	(0.034)	(0.024)	(0.019)
Employment Manuf				-0.391***	-1.682***	-1.177***	-0.720***
				(0.110)	(0.401)	(0.332)	(0.247)
R^2	0.146	0.180	0.168	0.197	0.225	0.218	0.264
Observations	666	674	674	662	670	670	670

Notes: Variable description is given in Table 1. The number of citations per inhabitants is averaged over the period 1998-2008 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. Cross section OLS regressions with CZs weighted by population. Regressions also include a dummy for being an urban CZ. Heteroskedasticity robust standard errors clustered at the state level are reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 16: Innovation and social mobility at the Commuting Zone level. Entrants and incumbents innovation and lobbying

Dependent variable	AM25				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of innovation	Cit5	Cit5	Cit5	Cit5	Cit5
Innovation					
by entrants	0.023**		0.019*	0.001	0.035***
	(0.009)		(0.009)	(0.007)	(0.012)
by incumbents		0.016**	0.006	0.001	0.004
		(0.008)	(0.007)	(0.006)	(0.008)
Gdppc	-0.081	-0.047	-0.086	-0.058	-0.087
	(0.057)	(0.064)	(0.058)	(0.108)	(0.054)
Popgrowth	-1.774**	-1.847**	-1.827**	-3.428**	-0.907
	(0.821)	(0.837)	(0.863)	(1.293)	(0.968)
Finance	0.018	0.017	0.018	0.032	0.015
	(0.018)	(0.019)	(0.019)	(0.025)	(0.021)
Government	0.035	0.039	0.035	-0.019	0.036
	(0.033)	(0.035)	(0.033)	(0.023)	(0.040)
Participation Rate	0.225	0.199	0.203	0.896**	-0.054
	(0.208)	(0.217)	(0.210)	(0.338)	(0.217)
Tax	-0.001	-0.001	-0.001	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
School Expenditure	0.010	0.007	0.009	0.015	0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Employment Manuf	-0.334***	-0.384***	-0.358***	-0.305***	-0.304**
	(0.109)	(0.113)	(0.113)	(0.110)	(0.125)
R^2	0.198	0.185	0.201	0.404	0.269
Observations	662	662	662	328	334

Notes: Variable description is given in Table 1. The number of citations per inhabitants is averaged over the period 1998-2008 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. Column 4 restricts to CZs above median in terms of lobbying intensity, where lobbying is measured as explained in subsection 8.2 while column 5 restricts to CZs below median. A dummy equal to one if the CZ belongs to an urban area is included but not reported. Cross section OLS regressions with CZs weighted by population. Heteroskedasticity robust standard errors clustered at the state level are reported in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.