# Idea Production and Team Structure

Jeremy Pearce*

University of Chicago

January 20, 2023

**Abstract**

Teamwork is the bedrock of modern innovation. This paper builds a framework that connects idea production in teams to aggregate innovation. I use this framework to quantify the sources and policy implications of the rise of teams in innovation. Most of this rise is due to the changing production function of ideas, consistent with ideas being harder to find. I use the calibrated model to study taxation and immigration policies in a team innovation economy. Using new data from the former Soviet Union and the fall of the Soviet Union as a quasi-experiment, I show how opportunities in teams induce self-selection in migration. I quantify the degree of self-selection, which helps explain the outsized role of immigrants in American innovation, the distribution of immigrant expertise, and informs immigration policies.

**Keywords:** Innovation, Endogenous Growth, Ideas, Inventors, Human Capital, Teams, Taxation, Immigration, Patents, Technology.

**JEL Classification:** O30, O31, O32, J22, J61.

*I thank Ufuk Akcigit, Steve Davis, and Nancy Stokey, for tremendous insight and support. Eliot Abrams, Stephane Bonhomme, Thomas Bournay, Santiago Caicedo, Michele Carter, John Grigsby, Ben Jones, Greg Kaplan, Bill Kerr, Ilse Lindenlaub, Josh Morris-Levinson, Karthik Nagarajan, Tom Nicholas, Marta Prato, Esteban Rossi-Hansberg, Gustavo de Souza, Stefanie Stantcheva, Stratton Tolmie, Alessandra Voena, Liangjie Wu, and Yulia Zhestkova have all provided valuable and insightful comments, as have participants in seminars at CREI, Harvard Business School, Southern Economic Association, and the University of Chicago.
Contact: `jgpearce@uchicago.edu`.

# 1 Introduction

Today's technological and scientific innovations rely heavily on teamwork, even in traditionally individualistic fields. According to mathematician Terence Tao, "Nowadays, most problems in mathematics are *interdisciplinary*. You need expertise from many different fields of mathematics or subfields outside mathematics. More and more, you need to collaborate."[1] While teamwork is at the center of modern innovation, there is no quantitative framework for understanding the sources and macroeconomic implications of the rise of teams. This gap motivates the following research questions: what are the sources behind the rise of teams in science and technology? Is it because ideas getting harder to find, which has negative implications for growth? Or are teams becoming more common because of falling communication costs, which has positive implications for growth? What new insights emerge from the modern team economy that inform policies such as taxation and migration?

This paper builds a framework that links the matching of *teams* with *differentiated expertise* to the overall direction and amount of innovation. I provide a quantitative model to understand i) the implications for growth of matching in different teams, ii) the sources behind the rise of teams in innovation, and iii) the policy implications of a team-led innovation economy, with a focus on immigration and taxation. I find that the majority of the rise of teams is due to the *rising relative value of teams vs. working alone*, which explains 68% of the rise in teams from the 1980s to the 1990s, and appears to be behind the continued rise. This result is consistent with the literature on ideas getting harder to find (Bloom et al., 2020), and the rise in the combinations of expertise required to produce new ideas (Jones, 2021; Akcigit et al., 2022).

The rising and persistent relevance of teams puts a premium on understanding innovation policies through a team lens. I focus on two policy exercises in this paper. First, I study the effects of taxation on teams through the sorting to teams channel. I find that a 10% tax on innovation profits could decrease aggregate innovation by as much as 7% by

[1] Author's emphasis, Tao (2017).

diminishing the incentives to sort into the best teams. Second, I use the team innovation economy to study migration patterns. I use new data from the fall of the Soviet Union as a historical case study. I find that Russian migration contributed about 50% more to aggregate innovation than would have been predicted in a model without self-selection and teams.

Innovation is the central determinant of long-run economic growth, and human capital is the central determinant of innovation. Thus, as teams become more important for innovation, they become more essential for generating and sustaining long-run growth. However, competing beliefs about the determinants of this rise suggest different interpretations and optimal policies. There is significant empirical evidence of both falling communication costs and ideas becoming harder to find. I frame this debate through some new facts in patent data from the US Patent and Trademark Office (USPTO). I present three facts, in addition to the general rise in teams, that suggest the need for a unified framework.

**Fact 1.** The impact of *teams with differentiated expertise* is rising over time.

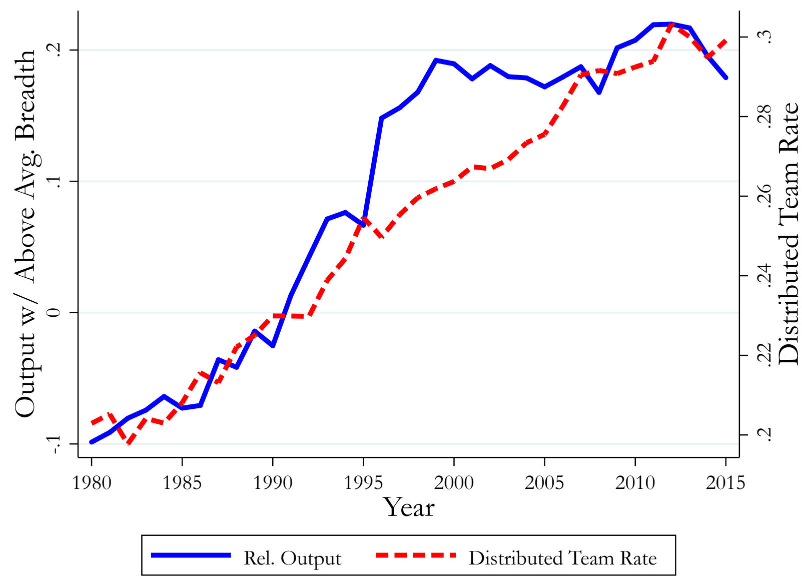
**Fact 2.** Team collaborations are becoming more geographically dispersed over time.

**Fact 3.** Immigrant inventors shape the technological composition of the economy (e.g., a large share of immigrant inventors push the frontier in computer technology).

Figure 1 presents Fact 1 and Fact 2. I plot the relative patent impact of teams above and below the annual average *breadth* of domain expertise (blue solid line and left axis), conditional on all inventors being in the same location.[2] Here, it signifies the number of unique patent classes in which an inventor has experience. For example, if the average team has 2.2 unique technologies of cumulative experience in a given technology class, then teams with 3 or more unique technologies of experience will be considered in the higher breadth group. The blue line increasing over time indicates that teams with a broader scope of expertise are becoming relatively more productive. Furthermore, the distributed team rate

[2] I define a measure of breadth in Section 3 that informs the expertise of types.

Figure 1: Rising Returns to Teams and Falling Communication Costs




(or rate of geographically separated teams, red dotted line and right axis) is also increasing, as the share of teams with inventors in two distinct locations is rising, corresponding to the right $y$-axis in Figure 1. Fact 3 applies ethnicity data to study the contribution of "likely" Russian migrants, discussed in Section 5, to find that immigrants are self-selected into certain technologies.

These three facts serve as a launching point for two threads of analysis. Fact 1 and Fact 2 point to two separate candidates for the *sources* of the rise in teams, whereas Fact 3 is important to understand the *implications* for immigration and innovation policies. Fact 1 and Fact 2 motivate a model where teams form based on the relative output of the team and the cost of forming the team. Team collaborations may rise due to either force (Fact 1 or Fact 2), and my calibrated model delivers the share of the rise of teams that can be explained by each force. In Section 5, I focus on how immigrant inventors selectively migrate depending on their role in American innovation. The paper proceeds in 4 steps to address and quantify the sources at play.

First, I build a matching-in-teams model that links the benefits and costs of a specific team to how often that team forms. The model allows for a quantitative decomposition of the roles of the three forces in determining the changing pattern of teams: i) the relative *benefits* of teams against working alone, e.g. the relative output of the idea or idea production function, ii) communication *costs*, and iii) *supply* or inventor composition. The model follows classic marriage models (e.g., Becker, 1973, adapted for quantitative work by Choo and Siow, 2006), and builds on this work by allowing for matching across teams of multiple sizes of any type (i.e., not restricted to two-sided markets). The model is non-parametric and thus is flexible to various matching patterns observed in the data.

Second, I use USPTO patent data to build measures of individual domain expertise that are based on the distribution of an individual's idea production across patent classes. This domain expertise measure allows me to analyze the interaction of individual expertise and team formation over time. The measures admit a parsimonious connection between the model ingredients of expertise types with differentiated skills and the data ingredients of differentiated experience of individuals across technologies.

Third, I connect the model to the empirical study of domain expertise to uncover patterns in team production. I quantify the contribution of the three forces by embedding the estimated production function and communication costs into the matching model. I compare the 1980s to the 1990s when evaluating the rise in team size, though this is part of a larger trend.[3] I find that changes in the benefits to teams or the idea production function explain the largest share of the increase in team size (68%). Falling communication costs, treated as a residual, also explain a significant portion of the rise in teams (41%). Another potential source of the rise of teams is the composition of inventors, e.g. supply. If chemists work in large teams and chemistry becomes a more innovative field, then team size would increase mechanically. Yet in the quantitative exercise, I find a negative effect of composition on the change in team size, contributing -9% to the observed increase.

The main driver of the rise in team size, the rise of the benefits to teams relative to working alone, is consistent with the proposition that ideas are getting harder to find. This is because the innovative impact of sole-inventors is declining over time, and this decline

[3] By restricting attention to the last decades of the 20th century, I avoid measurement issues regarding patent quality.

means the necessity to team up is rising. In this paper, I focus on citations and private value. These measures allow for comparison across patents, but do not fully capture the overall output generated by an idea.. However, if each idea is becoming less impactful over time, this is consistent with ideas getting harder to find as documented in previous work (Bloom et al., 2020).

Fourth, I explore policy applications within the team production and matching framework, with a particular focus on taxation and immigration policy. The team economy provides a new mechanism for thinking about how policies and aggregate innovation interact. Taxes and immigration address two different margins on the interaction of policies and innovation. First, looking at taxes conditional on an existing distribution of expertise focuses purely on how taxation affects sorting into innovative teams. Second, exogenous labor supply shifts show how H1B policies can affect innovation. My model provides a way to think through how skill-targeted policies interact with the economy. These two different margins address how inventors sort into teams and the overall expertise composition in the economy.

In an application of this policy exercise, I make use of new data and quasi-experimental evidence from the breakup of the Soviet Union. Russians consistently comprised around 0.6% of inventors in the US in until the early 1990s, but accounted for 1.4% of inventors by 2005. [4] Leveraging the rise of Russian inventors, I shock the composition of expertise in the United States with the predicted Russian expertise. To do this, I use patent records from the Soviet Union that illustrate how Russian expertise across technologies differed from US expertise across technologies in the decade before the breakup in 1991. My model predicts the self-selection in migration and team composition, which is verified through evaluating Russian inventor team composition. I also use this evidence to evaluate the model-implied contribution of Russians after the fall of the Soviet Union and find that the production in teams explains a significant component of their impact on US innovation. A standard model without self-selection in a team economy under-predicts the immigrant contribution by over

[4] I use ethnicities associated with the former Soviet Union as in Kerr (2007).

50%. The team channel is necessary to make a statement on the quantity of their overall contribution, and thus provides an important framework for understanding the innovation effects of migration.

**Related Literature**

This current paper focuses on the team foundations of ideas and economic growth. Economists have long known that ideas are the building blocks of long-run economic growth (Romer, 1990; Aghion and Howitt, 1992; Jones, 2005), with some papers stressing the role of human capital more intensively (Lucas, 1988; Jones, 2005; Lucas, 2009). Modern quantitative endogenous growth frameworks have moved to put human capital at the center of endogenous growth (Akcigit et al., 2018; Hsieh et al., 2019; Akcigit et al., 2020). However, the existing literature has not focused on the role of teams with *differentiated expertise*. As I discuss in this paper, there is significant evidence this is associated with the rise of teams. Empirically, teams are on the rise across both science and technology production (Wuchty et al., 2007). The implications for growth are positive if this is due to falling communication costs, but if this is due to ideas becoming harder to find and teamwork more necessary (Kortum, 1997; Weitzman, 1998; Jones, 2021; Akcigit et al., 2022), it may be associated with a long-run decline in growth if the inventor population is fixed, consistent with scale effects described by Jones (1995).

To put these questions in a quantitative environment, I build on work that applies tools from the classic Becker (1973) marriage paper to quantify how policies affect sorting into marriages Choo and Siow (2006). The paper also provides insights on the division of labor with skill heterogeneity (Becker and Murphy, 1992; Stokey, 2018). I stress the importance of expertise being both multidimensional and specific to certain knowledge domains, what Hayek (1945) considered the most essential feature of the global economy. The organization of an economy and the teams within it depends on this distribution of knowledge (Garicano and Rossi-Hansberg, 2006). In building the interaction of heterogeneous knowledge in teams into the matching process, my model builds on Choo and Siow (2006), who estimate a marriage model with transferable utility and heterogeneous preferences following Becker (1973) and McFadden (1974).

The quantitative question connects to more reduced form empirical evidence on the motivating forces behind the rise of teams. Various work points to the *relative benefits* of working in teams versus working alone rising over time due to the nature of expertise (Falk-Krzesinski et al., 2010; Bennett and Gadlin, 2012; Bikard et al., 2015; Teodoridis, 2018). Other work has documented the role of changes in communication costs fostering an increase in teamwork (Adams et al., 2005; Agrawal and Goldfarb, 2008; Kim et al., 2009; Forman and van Zeebroeck, 2012). While these explanations have been presented empirically as two central reasons for the rise of teams in innovation, there is no existing framework to incorporate and compare these forces quantitatively. Further, the team innovation economy with differentiated expertise has not been incorporated into the quantitative endogenous growth literature, even though teams represent the vast majority of modern contributions to science and technology.

Lucas and Moll (2014) and Perla and Tonetti (2014) focus on the choice to invest in learning versus production in driving aggregate innovation. Further, there have been empirical and theoretical frameworks providing evidence that skill breadth and depth and locational distribution matter for idea quality (e.g. Jones, 2009; Berkes and Gaetani, 2019). While idea heterogeneity serves an important role in the endogenous growth literature, its roots in domain specific human capital and individual interaction have received less attention. Yet, heterogeneous human capital is at the core of heterogeneous ideas.

Disciplining the role of expertise in teams and innovation has many potential applications. This paper primarily directs its attention to taxation and immigration policies. On taxation, I connect to a burgeoning literature that focuses on the interaction between taxation and innovation (Akcigit and Stantcheva, 2020; Akcigit et al., 2021; Jones, 2022), with this paper pointing to how taxes affect sorting into teams. I build on a literature that delivers conflicting accounts of the role played by immigration in idea production. In one study, Borjas and Doran (2012) find that Russian mathematician immigrants substituted for US mathematicians in idea production in mathematics. In another study, Moser et al. (2014) find positive spillovers from German-Jewish chemist emigres. Historically, immigrants have had a significant impact on American technology (Akcigit et al., 2017). Immigrants are more concentrated in patent-heavy fields, leading them to be more innovative than natives (Hunt and Gauthier-Loiselle, 2010). Given the significant moving costs, it makes sense that immigrants who move self-select into productive fields (Borjas, 1987). In regards to policy, Kerr and Lincoln (2010) find that increases in the H1B cap spurred innovation. In this paper, I stress that the team production channel is essential for understanding how immigrants interact with a country's existing expertise to shape overall output. I find that the geographical distribution of individuals still has first-order implications on the prevailing team structure and economic growth, which suggests that policies related to immigration continue to be an essential ingredient in innovation. Addressing horizontal skill differentiation is crucial in exploring the interaction between immigrant and native expertise.

The key conceptual point of this paper is that, with teams on the rise, growth economists must build in quantitative models that take the team element seriously. More specifically, a team is a *joint effort* with *non-partitionable output*. This team structure has been emphasized in the economics literature for 50 years (Alchian and Demsetz, 1972; Marschak and Radner, 1972). More recently, empirical evidence from surprise deaths has shown team complementarities are significant (Azoulay et al., 2010; Jaravel et al., 2018). I add to this discussion by focusing on the domains of expertise and cross-expertise collaboration. This will be front and center as I turn to the theoretical and empirical analysis.

The rest of the paper is organized as follows. Section 2 builds a team production model that links the value of teams to their observed frequency. Section 3 introduces the USPTO data and and explains how I construct the measures I use in my empirical and quantitative analysis. Section 4 discusses the quantitative decomposition of the role of each force in driving the change in team size. Section 5 illustrates the ability of these results to elucidate policy questions, and focuses on taxation and immigration policy in particular. Section 6 and Appendix D discusses the general robustness of the results from the previous sections. Section 7 concludes.

# 2 A Model of Idea Production and Team Formation

I develop a model of inventors who match in teams, produce ideas, and share the returns. Inventors observe the set of possible teams they can join and make a decision to join based on the payoffs. This model embeds the intuition of the three forces discussed in the previous section that determine the matching pattern: the benefits to teams, the costs of team formation and communication, and the supply of expertise.

The model follows a similar structure to Choo and Siow (2006), who use matching pairs in a two-sided framework to infer the value of a marriage. Here, the model is extended to a situation in which agents can take any role in a team; that is, agents can match with any other inventor and in multi-inventor teams. This fits the market for invention, as inventors often match in large teams and match with inventors of the same "type" as themselves (e.g. chemists work with chemists). I also allow for any possible team match up to a given size, to allow for many teams of differentiated expertise, (e.g., chemists, biologists, and computer scientists team up).

## 2.1 Environment

There are a mass of inventors $M_x$, where each individual is one of a discrete number of skill types or expertise. A skill type is indexed by $x \in \mathbb{X} \subset \mathbb{R}^S$. While $x$ is one of a finite number of types, $x$ contains a vector of length $S$ which signifies the $S$ domains of expertise that can be utilized to produce patents. The expertise of team members matters for the quality and domain of patent production.

The inventors are risk-neutral and maximize linear utility in their wage and an idiosyncratic preference shock in a static setting. Inventors can either join a team up to some size $\overline{T}$ or work alone. Due to the finite team size $\overline{T}$ and finite number of types $x$, there are a finite number of total team types.

A team is indexed by $k = \{x^1, ..., x^T\}$. Team $k$ generates output that is a function of the vector of skills of each type on the patent. The production functions for each team and individuals working alone are:[5]

$$q_k = q(x^1, ..., x^T) \qquad ; \qquad q_{\underline{k}}(x) = q(x^1). \tag{1}$$

Each operating team needs to pay a cost to communicate that depends on the team type, $c_k$. This cost can be understood as the cost of communicating on a project or the cost of forming the team. The communication cost for a single inventor working alone is zero; for multi-person teams, communication costs are flexible and inferred from the data,

$$c_k = c(x^1, ..., x^T) \qquad ; \qquad c_{\underline{k}} = 0. \tag{2}$$

Each team of inventor types has a corresponding total net output, $q_k - c_k$, while the net output for individuals working alone is $q_{\underline{k}}(x)$. Individual types are assigned in the amount  to a specific team type $k$. For instance, in a team with two of type $x, = 2$. For each individual type $x$ on team $k$, the total output is shared such that there is no output left on the table. This means that the total wages paid out to team members is equal to the total team output:

$$\sum_{C(x) \in k} w_k^x = q_k - c_k. \tag{3}$$

Having discussed the net team output, $q_k - c_k$, and a general condition on wages, I turn to the individual's problem of choosing her team.

[5] Teams also choose a patent technology class to work in. Given the team members, this optimal class immediately follows. Because this immediately follows from the team composition, I leave this out of the model. I will be more specific about this problem when I map this model to its empirical counterparts in Section 6.1.

**The Individual's Problem**

Individual $i$ is an infinitesimal agent of type $x \in \mathbb{X}$ who derives systematic and idiosyncratic utility from working in team type $k$. The systematic component, $w_k^x$, is a result of market forces and is the same across all types $x$ within a given team $k$. The second component, $\epsilon_k^x(i)$, is an iid preference shock for working in team type $k$ which is specific for a given individual $i$ of type $x$. This idiosyncratic iid individual-by-team utility is drawn from an iid type-I extreme value distribution. This shock represents heterogeneous and unobserved reasons for forming teams. The distribution of the shocks is not related to the systematic observable component of an agent's skills. These shocks follow a cumulative distribution function as in McFadden (1974):

$$F(\epsilon) = \exp\left(\exp\left(-\frac{\epsilon}{\phi}\right)\right).$$

Each inventor $i$ of type $(x)$ has the option to either work by herself or join a team. If she decides to work by herself, her team is indexed by $\underline{k}(x)$. If she decides to work with someone else, she can be matched with $\tilde{k}(x)$ team types, indexed by the other team member's type. Denote $K(x) = 1 + \tilde{k}(x)$ as the number of team types an individual of type $(x)$ can join. Due to the upper bound on team size $\overline{T}$ and finite number of types in the economy, there is a discrete set of team types $i$ can join. Individual $i$ observes a set of shocks across the team types they can join as follows,

$$\boldsymbol{\epsilon}^x(i) = \{\epsilon_k^x(i) : k \in K(x)\}.$$

For each $i$ of type $x$ there is a return equation for joining each team $k$,

$$\pi_k^x(i) = \underbrace{w_k^x}_{\substack{\text{systematic} \\ \text{component}}} + \underbrace{\epsilon_k^x(i).}_{\substack{\text{idiosyncratic} \\ \text{component}}} \tag{4}$$

Each individual $i$ of type $(x)$ chooses her team $k$ to maximize her return, $\pi_k^x(i)$. This is part of the equilibrium that is discussed next.

## 2.2 Equilibrium

The equilibrium is a set of wages across teams, the mass of individual types assigned to teams, and the mass of teams, $\{w_k^x, m_k^x, m_k\}$. The wages emerge as a result of the trading game to clear the market for each type and in each team. The endogenous assignment of types to teams, $m_k^x$, emerges from this process. The mass of a given team, $m_k$, is the mass of assigned types to the team divided by the number of unique team members.

The equilibrium is characterized by each agent solving their optimization problem, and the market clearing within each team and within each type. The resulting equilibrium has a sharing rule within each team type, and frequency of each observed team type. I explore the empirical counterpart to each equilibrium object in greater detail in the quantitative section, where I map the model to patent data. I focus on the mass of each team $m_k$, the net return to each team $q_k - c_k$, and the expected value of being a given type (Proposition 2). Tracking these objects helps evaluate the changing patterns across teams and the effects of subsidies and expertise shocks on the economy.

Agent $i$ observes her vector of idiosyncratic shocks and the systematic return to working for each team. She then chooses the team $k$ that delivers the maximum return. Wages are determined endogenously by market clearing in teams for all types. There are five equilibrium conditions.

**Definition of Equilibrium.** Equilibrium is defined as a set of sharing rules (wages) and allocations that adhere to individual-level optimization market clearing. I go through the optimization problem, wages, and allocations in turn.

- *Optimization:* Each $i \in \mathbb{X}$ chooses the team $k^*$ to maximize the sum of her idiosyncratic and systematic income,

$$k^*(i) = \arg\max\{\pi_k^x(i) : k \in K(x)\}.$$

This maximization delivers a relationship between wages and allocations that is governed by the dispersion of the preference shock $\phi$ and the mass of a given type $(x)$, $M_x$,

$$m_k^x = M_x \frac{\exp(w_k^x/\phi)}{\sum_{\tilde{k}\in K(x)} \exp(w_{\tilde{k}}^x/\phi)}. \tag{E1}$$

- *Sharing Rules:* Wages for each agent on the team add up to total net output for each team $k$:

$$\sum_{x\in k} w_k^x = q_k - c_k. \tag{E2}$$

- *Market Clearing and Symmetry:* Markets clear for each inventor type $(x)$ (E3), the mass of each type assigned to each team is equal to the mass of the team multiplied by the number of this type on the team (E4), and there are no teams with negative mass (E5):

$$\sum_{k\in K(x)} m_k^x = M_x \qquad \forall \quad x, \tag{E3}$$

$$m_k^x = m_k \qquad \forall \quad x \in k, \tag{E4}$$

$$m_k^x \geq 0 \qquad \forall \quad x \text{ and } k. \tag{E5}$$

Proposition 1 follows from the equilibrium conditions.

**Proposition 1.** An equilibrium that satisfies (E1)–(E5) delivers a relationship between the (i) masses of each team type $k$ to (ii) the idea production function, (iii) the communication costs, and (iv) the supply of types as follows,

$$\overbrace{\sum_{(x)\in k} \log\left(\frac{m_k}{m_{\underline{k}}^x}\right)}^{\text{(i)}} = \frac{\overbrace{q_k - \sum_{(x)\in k} q_{\underline{k}}(x)}^{\text{(ii)}} - \overbrace{c_k}^{\text{(iii)}}}{\phi} \qquad \text{s.t.} \qquad \overbrace{\sum_{k\in K(x)} m_k = M_x}^{\text{(iv)}}.$$

*Proof.* See Appendix A.1. □

Proposition 1 links inventors' sorting in teams to the values of those teams; in particular, it relates the mass of a given team, $m_k$, relative to each type working alone to the value of the team $q_k$ relative to working alone. Team frequency moves in a log-linear way with team output. As each agent becomes less productive alone $(ii)$, or the communication costs decrease $(iii)$, the team will form more often relative to each agent working alone. This framework provides the launching point of this paper. I use this framework to quantify the forces behind the rise of teams and enable counterfactual studies, as $(ii)$, $(iii)$, and $(iv)$ are linked to the benefits of teams, costs of teams, and supply of talent respectively.

Let me be explicit about what I am trying to capture and quantify with this model. There are three pieces of the model that shift from the earlier period (e.g., 1980s) to the later period (e.g., 1990s). First, the idea production function $q_k - \sum_{(x)\in k} q_{\underline{k}}(x)$ may shift. Combinations of certain team types may yield different returns over time. At times, hardware producers see higher returns to working alone versus pairing together, or pairing up with a chemist.

Second, individual team types may face changing communication costs over time, $c_k$. For instance, with the advent of email and file sharing, inventors in separate locations can more easily produce together. This ability could drive down the costs of forming certain teams over time.

Third, the composition of inventors ($M_x$) may change. In particular, the 1990s saw a large movement toward fields related to computing, information storage, and hardware. This was driven by two forces beyond returns and costs. First, inventors selected into advanced degrees in these fields. Second, immigrant talent arrived with expertise in those fields, impacting the composition of inventors. Reductions in immigration restrictions in the US and corresponding outflows from Russia and China generated a large influx. As a result, the inventor composition in 2000 differed from the inventor composition in 1980. In Section 5, I discuss the influence of this migration and the role of self-selection. The following proposition will be an important reference.

The last result of this section characterizes the expected value of being an inventor of type $x$, which serves as an important statistic for informing immigration patterns and self-selection. This statistic for valuing types delivers an intuitive and, as seen in Section 5, sensible predictor of the types that are the most productive in a large economy of teams. Proposition 2 discusses the properties of the ex ante value of being a specific type.

**Proposition 2.** The expected value for an agent of type $x$ before her preference draws is as follows:

$$\mathbb{E}[V_x] = cons + \underbrace{q_{\underline{k}}(x)/\phi}_{\text{output alone}} + \underbrace{\log\left(\frac{M_x}{m^x_{\underline{k}}}\right)}_{\text{concentration in teams}}. \tag{5}$$

*Proof.* See Appendix A.1. □

There are two components of the private value of being a given expertise type $x$. First, inventors that produce higher impact patents alone have higher value ex ante. Second, conditional on productivity alone, inventors who are frequently in teams receive relatively higher returns in teams. The respective weight is adjusted by the shock dispersion $\phi$. This result is important for evaluating how self-selection impacts inventor migration in Section 5.

Section 4 uses the model framework to quantify the contribution of three key forces on the changes in the matching pattern. These three forces, returns, costs, and supply, exemplified by $q_k - \sum_{(x)\in k} q_{\underline{k}}(x)$, $c_k$, and $M_x$, impact the allocation to teams, $m_k$. Section 5 applies this framework to policy counterfactuals with a particular focus on immigration policy. I first discuss the data and build a bridge from the empirical framework to the quantitative analysis.

**Data-Relevant Objects: Sources of Rising Teams.** To summarize the important objects in the data, I am interested in characterizing the expertise distribution $\mathbf{M}$, the sorting into specific team types $m_k$, the value of each team $q_k$, and communication cost $c_k$. These objects from Proposition 1 link the overall matching pattern to underlying team fundamentals.

In the data, I focus on $q_k$ through citations and stock market value. I focus on $c_k$ through the residual team formation in addition to geographical team dispersion. Finally, I focus on $\mathbf{M}$ and $\mathbf{m}$ through measures from USPTO patent classes, and inventor and team identifiers.

**Data-Relevant Objects: Implications of Rising Teams.** To understand the determinants of sorting and output, policies must take into account counterfactuals in a team economy. First, Proposition 1 shows how the sorting pattern would respond to taxes and subsidies of team types. More relevant for self-selection in migration, Proposition 2 details the private value to an individual of expertise $x$. This value has two components. First, the output from working individually, as higher output indicates higher private value. Second, the more frequent an expertise is in teams, conditional on productivity alone, the higher the return to that expertise. This object can be brought to data since both the productivity of inventors working alone and the frequency in teams can be observed. This allows me to predict self-selection in migration policy as discussed in Section 5.

# 3 Data and Measurement

The data will inform the model ingredients in order to quantify the sources and implications of teams in the quantitative exercise. This section discusses the data sources and relevant measures of expertise in the data. I then discuss measures of communication costs.

## 3.1 Data Sources

I use four data sources in my analysis. First, I rely on USPTO patent data with inventor information disambiguation to track inventors and build expertise vectors. Second, I merge this patent data with patent value data from other papers (e.g., Kogan et al., 2017) to ensure robustness to patent output measures. I introduce new data from the former Soviet Union from 1924–1993, which details the technological domain of innovations in the Soviet Union. These innovations followed a different distribution than US innovations in the

1980s prior to the fall of the Soviet Union, and and they provide a benchmark for analyzing the contribution of Russians to US innovation during the large immigration period of Russian inventors in the 1990s. Lastly, to identify Russians in the data I apply an algorithm that delivers the expected probability of ethnic origin by country with data from Kerr (2007).

**USPTO Patent Data and Inventor Disambiguation Algorithm.** Although this paper uses several distinct data sources, it primarily relies on USPTO patent data with patents granted from 1976 to 2015. On inventors, the USPTO states, "US patent applications must list the 'true and only' inventors." A patent $p$ is characterized by a technology class $s$, a team of inventors who jointly produce the patent, and forward citations, a proxy for patent value.[6][7]

Li et al. (2014) provide a dataset for inventor identification that links the entire career of an inventor to her history. They use a Bayesian disambiguation algorithm that employs patent class, firms where an inventor works, and her corresponding co-authors to track the full history of individuals on patents. The two main problems these algorithms deal with are cases of misreportings (e.g., misspellings such as "Jonh Smith") and common names (e.g., "John Smith"). The ability to identify inventors over time is crucial for building expertise measures that can speak to how inventors contribute to a team.

All types of assignees — firm, international, university, and government — are included. I truncate the data on both ends to capture experience vectors of individuals and clean citation data. The quantitative and empirical analyses focus on years 1980–2000, but inventor expertise vectors use data starting in 1976. I also discuss how the results fit with the ongoing changes in patenting up to 2015. The resulting sample includes 2.2 million unique patents, 1.5 million unique inventors, and 4.5 million patent $\times$ inventor observations.

The technological class system and citation network admit identification of technolog-

[6] USPTO assigns a primary technology class in USPTO and WIPO assigns a primary IPC classification.

[7] Patent stock market value and renewals are also used as a measurement of patent value in robustness checks.

ical areas where inventors operate, or their areas of expertise. For my measurement of expertise, I take a stand on which level of classification to use for evaluating expertise. This paper explores three potential levels of classifications. The primary empirical analysis is done at the International Patent Classification 3-digit level (IPC3) for more granularity, but the quantitative analyses are done at the IPC2 level to have enough data for each type.[8] I also focus on USPTO classification measures in the empirical analysis robustness in Appendix B. The qualitative results do not shift significantly depending on the level of classification.

I use log of the average citations by the team as my measure of output quality, but test other measures in Section 6 and Appendix B. I adjust for patent truncation using IPC1 patent class and the date of application in order to compare citations across different classes and time periods, following Hall et al. (2001). I renormalize the value of sole-authored patents each period in order to have a similar benchmark, but I analyze other measures in Section 6 and Appendix B.

**Patent Value.** First, to ensure that patent citations are picking up similar outcomes to patent value, I merge in patent stock market value measures from Kogan et al. (2017). This measure delivers the projected value of a patent based on the change in stock market value on the day the patent was granted. This data is available for a limited set of patents, since it requires the firm be publicly listed. Nevertheless, it serves as a good verification exercise for observing the response of patent value to depth and breadth.

**Records from the Soviet Union.** To apply the model to immigration counterfactuals and verify its qualitative results, I make use of a novel dataset from the former Soviet Union. This dataset contains patent records from all inventions from the Soviet Union from 1924–1993. These documents are provided by Rospatent (Russian Federal Institute of Intellectual Property) and the Federal Institute of Industrial Property (FIPS).

FIPS provides all the data in the form of DVDs that contain complete scans of patent

[8] Appendix B.2 provides an example of the different levels of classification.

documents granted in the Soviet Union. Because the Soviet Union was essentially uninvolved in global technology production, this dataset provides a unique insight into the technologies produced in the Soviet Union. The DVDs record a total of 1.4 million unique documents.

There were two main types of patent documents in the Soviet Union: a patent and a certificate of authorship. A certificate of authorship was the most common patent document. These documents did not give an inventor the exclusive right to an invention, but the government awarded prizes for inventions. One essential component of this data is the technological patent classes. The FIPS records contain IPC patent classes, following the same format as USPTO patents. My main goal with this data is to understand the domain of expertise of Soviet inventors at the time of the fall of the Soviet Union. As a result, I use the most recent innovation decade from the Soviet Union (1980s).

For the shock to be treated as quasi-experimental, it is necessary that inventors in the Soviet Union did not choose to innovate technologically with the expectation that their expertise as inventors would be integrated into the US market. This seems sensible given the unexpected nature of the fall of the Soviet Union and the fact that specialized human capital takes significant time to build. I discuss this further in Section 5, which addresses self-selection in migration.

**Ethnic Origin.** To match the ethnicities of inventors on patents for the purposes of both tracing out the ethnic diversity of inventors and matching ethnic Russians, I adopt the probabilistic ethnicity matching algorithm from Kerr (2007). This algorithm exploits the fact that certain names are common for certain ethnicities (e.g., "Wu" as Chinese or "Rodriguez" as Hispanic). The match rate for each name to an ethnicity is 80%. With this data, I find that Russian inventors jump from 0.7% of all US patents to 1.4% from 1991–2005. Next, I turn to the measurement of inventor and team expertise, which is important for the empirical analysis and quantitative results.

### 3.2 Data Measurement

This section constructs the empirical measures that I use in the empirical and quantitative analysis. I start by building the measures of individual and team expertise and then discuss how measures at the individual-level contribute to measures at the team-level.

**Inventor Expertise.** Inventors hold skills that they deploy in the production of patents in teams. Because individuals work in teams, it can be challenging to extract their domain of expertise from team production. For my expertise measure, I take the most prominent class of an individual, adjusting by patent quality $q_p$ (citations) and team size $T_p$ for expertise in class $s$ as follows,

$$x_s = \sum_{p \in s} \frac{q_p}{T_p}. \tag{6}$$

This expertise measure takes the count of an individual's patents in each class divided by the team size of the inventors on the focal patent ($T_p$). The adjustment by team size down-weights expertise measures in large teams as individuals are less likely to have expertise in the relevant area. Additionally, I explore inventor types only using data from their *sole-authored patents* in Section 6. Both sole-authored patenting and overall patenting deliver the same general result on the idea production function.[9]

**Definition 1.** *inventor expertise in class $s$.* Expertise in technology $s$ is given by an individual's total productivity in class $s$, $x_s$, net the focal patent.

**Definition 2.** *inventor skill type $x$.* Inventor $i$ is skill type $x$ if $\arg\max(x_1, x_2, ..., x_S) = x$.

For testing of the quantitative mechanism, I apply the skill from each class for individuals. However, for much of the quantitative question on the rise of teams, it is sufficient to treat individuals as having a main expertise that is associated with a bundle of knowledge. This comes from Definition 2.[10]

[9] I explore other measures in Section 6 and Appendix B. I discuss the counts in Appendix B.3.

[10] To better understand the mechanism, Section 6.1 leverages an individual's bundle of skills as inputs into the idea production function.

**Team Types.** When individuals work in teams, they combine their expertise. For instance, if one individual has expertise $x$ and another has expertise $y$, they can form a team $k = (x, y)$ to produce output $q_k$. Individuals have a single expertise or skill type, but the type may contain a broad vector of expertise. This logic follows a similar structure to the model. A team is a vector of individual types across skills (e.g., technology class expertise). Given that teams form either to take advantage of deep or broad knowledge, I direct attention to team *depth* and team *breadth*, which measures the team skill on the focal patent.

**Definition 3.** *Team Depth.* For a given team in technology $x$, team depth is the amount of expertise in $x$. This takes the sum of the individuals' impact within the focal patent class.

**Definition 4.** *Team Breadth.* Team breadth is defined as the sum of expertise represented on a given patent outside of the focal class. Increasing breadth implies teams from more diverse expertise backgrounds.

Teams may form in order to make use of depth and breadth of expertise. Further, the changing nature of teams may generate changing returns to both of these forces. While teams form to take advantage of specific skills, the summary of team breadth and depth will help express the underlying causes of the rise in teams and specify an idea production function. The analysis in this paper is done at the IPC2-level.

**Communication Costs.** The main section of this paper focuses on communication costs as the residual driving team formation that is not embedded in changes in the production function. However, there are two nuances to this interpretation. First, in a calibration in Appendix D, I look into the rise of team size explained by communication in distinct regions, and find this explains 25% of the increase in teams from the 1980s to the 1990s, and can likely explain a similar share today. I find that this is reasonably close to the residual estimate, which is correlated with other aspects of communication costs (e.g., expected distance, or skill distance).

# 4 Quantitative Analysis

This section builds the quantitative and empirical framework that I use to study of the rise of teams and policy counterfactuals. I build a bridge from the matching model from Section 2 to empirical measures from Section 3. First, I outline the quantitative infrastructure for studying the sources and implications of the rise of teams. Second, I quantify the contribution of each force (benefits, costs, inventor supply) employing the expertise measures from Section 3. Section 5 studies the implications of this framework in the context of immigration and taxation.

For the measures of expertise and individual type, I follow Definition 2. This takes the maximum expertise level per individual. For the bundle of skills associated with a given type, I take the average skill for each type across the range of technology classes. This allows for measurement of the expected impact of each team type within a finite set of teams.

## 4.1 Quantitative Framework

This section maps the three main forces from the model (benefit, cost, supply) into data-relevant components. The following equation links an outcome of interest, the mass of each team type $k$ (log count) to: (i) the relative *benefits* of teams, or the idea production function, (ii) communication *costs*, and (iii) the *supply* or composition of types. Equation (7) summarizes the relationship between the frequency of a team type and its relative returns:

$$\overbrace{\sum_{x\in k} \log\left(\frac{m_k}{m_{\underline{k}}^x}\right)}^{\text{log team count}} = \frac{\overbrace{q_k - \sum_{x\in k} q_{\underline{k}}(x)}^{\text{(i) benefits}} - \overbrace{c_k}^{\text{(ii) costs}}}{\phi} \qquad \text{s.t.} \quad \overbrace{\sum_{k\in K(x)} m_k = M_x}^{\text{(iii) supply}}. \tag{7}$$

The mass of each team $k$ is given by $m_k$, where the mass of type $x$ assigned to $k$ is $m_k$. The relative benefit to teams in production comes from comparing the production in the team, $q_k$, to solo production for each type, $q_{\underline{k}}(x)$. The communication costs enter separately from the skill and are thus considered in the residual. I perform exercises that correlate this residual with other measures of communication costs, and I find that communication costs explain a large share of the residual.

Equation (Q1), which puts Equation (7) in regression form, and Equation (Q2) are the main equations for the quantitative analysis. These equations relate the estimated production function and communication costs across teams to the relative frequency of observing the team in the data (Q1), and estimate the underlying returns to teams on the expertise of inventors (Q2). I use the estimated production parameters that link the types of teams $k$ to predicted relative output $\tilde{q}_{k,t}$ from Equation (Q2). I evaluate these two equations in the 1980s and 1990s:

$$\tilde{m}_{k,t} = \tilde{\beta}_0 + \tilde{\beta}_1 \tilde{q}_{k,t} + v_{k,t}, \tag{Q1}$$

$$q_{p(k,s),t} = \alpha_{0,t} + \sum_{j=1}^{5} \alpha_{j,t} \mathbb{I}\{Quint(D_{k,s}) = j\} + \sum_{i=2}^{5} \zeta_{j,t} \mathbb{I}\{Quint(B_{k,s}) = j\} + u_p. \tag{Q2}$$

I discuss Equation (Q1) and Equation (Q2) in turn. Equation (Q1) links estimated production function and the cost to the matching pattern. I classify types as discussed in Section 3.2 in order to estimate Equation (Q1). The components of Equation (Q1) are:

$$\tilde{m}_{k,t} \equiv \sum_{x \in k} \log \left( \frac{m_k}{m^x_{\underline{k}}} \right),$$

$$\tilde{q}_{k,t} \equiv q_{k,t} - \sum_{x \in k} q^x_{\underline{k},t}.$$

Equation (Q2) estimates the net benefit of team $k$, $\tilde{q}_{k,t}$. Equation (Q2) is estimated at the patent level, where I take quintiles of team depth and breadth. The coefficients on these respective quintiles, $\alpha_{j,s}$ and $\zeta_{j,s}$, are estimated within each IPC1 technology class. I fix the quintiles to match the entire time period 1980–2000. This captures the fact that different technology classes exhibit different returns to team skills. Equations (Q1) and (Q2) are estimated over two periods, the 1980s and the 1990s.

**Model Match.** Individuals are identified by their type, which includes a domain of expertise $x$. The mass of individuals of each type is given by $M_x$. For the quantitative decomposition, I split the sample into two distinct periods and rerun the model on those different time periods where individuals are identified through their patent production as in Equation (6).

Individuals have one expertise, which is their primary technology background (e.g., where they have produced the most patents, with focus on patents by inverse team size). To group people into types, I take the average bundle of skills per type.[11]

The fact that individuals operate jointly in teams and alone provides a lens to understand the domain of expertise while also learning how domain expertise contributes to team production. In particular, if chemists that provide valuable technological insights to pharmacology *only* work in pharmacology, it becomes challenging to categorize them as chemists. However, in productions with smaller teams, we should expect the productions to be more core to the individual's domain of expertise.

## 4.2 Quantitative Results

Before delving into the results, I discuss the intuition of how the quantitative framework elucidates the mechanisms discussed in this paper. I use the quantitative results to evaluate the three forces that could be changing the nature of teams, *benefits*, *costs*, and *inventor supply*. I will focus on the intuition of the relative *benefits* of teams, as this will be the primary mechanism of investigation in this section. I estimate two different production functions of ideas in the 1980s and 1990s and estimate the matching function in both periods as well. I ask what is the predicted change in team size from *only* changing the production function, and observe what overall team size this predicts.

Changes in the *benefits to teams versus working alone* come from changes in the idea production function, $q_k - \sum_{x \in k} q_{\underline{k}}(x)$, for different types $x$. As individuals become less

[11] Additionally, individuals can only have one location which comes from where they primarily file patents (home address). I review how this correlates with the variation attributable to communication costs in Appendix D.

productive alone or teams generate higher quality patents, individuals will form in teams more often. The strength of the response is governed by the dispersion of the preference shock $\phi$. In Equation (Q1), $\tilde{\beta}_1$ governs this responsiveness. There are two main sources within the idea production function that could be driving the changes in team size through the idea production function. Teams may exhibit larger returns to depth—ideas require deeper expertise and so inventors choose to form teams with those somewhat similar to themselves. Second, teams may exhibit larger returns to breadth—ideas require more expertise from different patent classes, so inventors work with those not in the same class.

I discuss how the observable response in output to both breadth and depth of expertise emerge in Section 6.1. In this section, I use the estimated production function of ideas based on the average level of skill within each expertise type. Having illustrated the match between the estimated and realized production function, I turn to the quantitative properties of how production and cost are linked to matching from Equations (Q1) and (Q2).

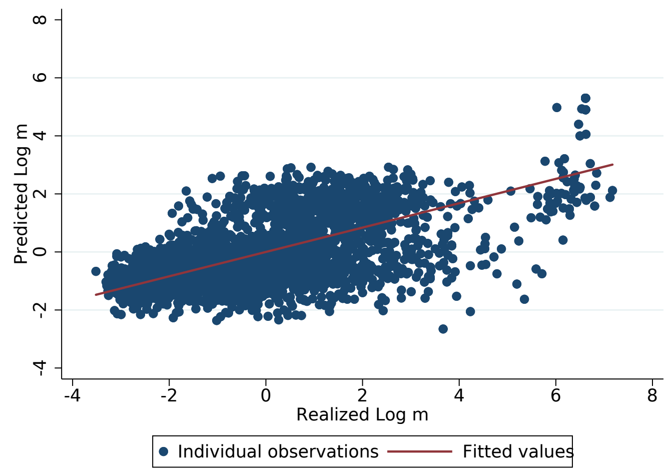
Table 1: Parameter Values

| **Parameter** | **Description** | **Value** | **Main Identification** |
|---|---|---|---|
| | | *— Panel A. From Production Function —* | |
| $\alpha_{j,s,t}$ | Quartiles of depth in patent class $s$ | $4 \times$ num. major tech $\times$ 2 periods | Production Estimation (Q2) |
| $\zeta_{j,s,t}$ | Quartiles of breadth in patent class $s$ | $4 \times$ num. major tech $\times$ 2 periods | Production Estimation (Q2) |
| | | *— Panel B. From Matching Function —* | |
| $\phi$ | Preference shock dispersion | $0.49^{***}$ | $\tilde{\beta}_{1,t}$ from Equation (Q1) |

*Notes:* This table describes the estimation and parameter values in the quantitative analysis. Column (1) indicates the parameters from Equations (Q1) and (Q2). Column (2) describes these coefficients. Column (3) provides the value or number of parameters (if more than one). Column (4) indicates the method of identification.

In addition to the production function, the key additional variables of interest in the quantitative procedure are the coefficient on coordination costs $\beta_c$ and the dispersion of the preference shocks $\phi$. Figure 2 illustrates how the model matches the data. Here, I take the fitted values of the team from the previous equations and plot them against the realized team matches. The $R^2$ is 0.43.

Figure 2: Production, Cost, and Realized Frequency of Team Type




*Notes:* This figure plots the predicted and realized density of each team type in both periods in the quantitative model. Equation (Q1) lists the log relative count of each team ($x$-axis) and Equation (Q1) predicts the relative share of each team ($y$-axis). This relationship is untargeted beyond the parameters from Table 1. The $R^2$ is 0.43. Source: USPTO and author calculations.

A point worth stressing from Figure 2 is that the predicted and realized matching has no mechanical relationship. This is because the model only delivers coefficients that govern the noise $\tilde{\beta}_1$. The positive correlation comes from linking the expected returns and the matching pattern. Overall, teams with higher expected returns are more likely to match. This is unsurprising, but does not directly follow from any mechanical assumptions.

**Results: Idea production function, communication costs, and supply of skill.** Once I estimate the parameters governing the production and matching equations, I apply each channel individually to understand its contribution to the change in team size. Intuitively, individuals match in proportion to patent quality in the pre-period and I estimate how closely these outcomes align. Once I have this estimated parameter, I allow the quality by itself to change and ask how much of a change in team size would this predict?

I start with a counterfactual analysis in order to understand the contribution of each force to the change in team size. I run the model separately for two periods in order to uncover the changing parameters. I ask how much would the size of teams change if only there was a change in the production function. In the case of the benefits of teams, I keep the parameters from the production function pre-period ($\alpha_{j,s,t}, \zeta_{j,s,t}$) and compare the realized team size to the counterfactual team size. I do the same thing with the coefficient on communication costs ($\tilde{\gamma}_t$) and the shares of types ($M_{x,t}$). Table 2 shows how much of the change in team size these three forces can explain.

Table 2: Contribution of each force to changes in matching pattern

| **Causal Force** | **Share of Change in Explained** |
|---|---|
| Benefit (Teams versus alone) | 68% |
| Cost | 41% |
| Composition | -9% |

*Notes:* This table runs the model as described in the main text and asks how much each force contributes to the observed share in team size. Source: USPTO and author calculations.

Changes in the idea production function can explain 68% of the change in team size from the 1980s to the 1990s. Composition pushes in the other direction in the quantitative exercise, driving -9% of the change according to IPC2 classifications. Assuming the residual increase in team size is due to changes in the costs of communication, I find that 41% of the increase in team size is due to a fall in communication costs, which emerges through the increase in teams unaccounted for by the increase in patent value.[12]

This section presented evidence that changes in the idea production function are the most important force behind the changes in team size. This means that there is an increasing premium on understanding policies that foster complementary expertise in teams. I turn next to policies that take into account this environment and the implications in particular for taxation and immigration.

[12] Appendix D addresses how measures of distance are correlated with this unaccounted for variation.

# 5 Policy Applications

The previous section built a framework to quantify the sources behind the rise of teams. Further, I illustrated that the rise of teams is connected in a significant manner to changes in the idea production function. In general the rise of teams, and the rise in their joint output, implies that team production is an essential aspect of innovation policy analysis. The framework in this paper is amenable to a wide variety of policy analyses. What does this imply for economic policy? How does taking teams and matching seriously affect classical policy issues, such as taxation and immigration?

I focus on taxes in Section 5.1. I then turn to high-skilled immigration, making use of the fall of the Soviet Union as a historical episode in Section 5.2. In Appendix C, I discuss more general lessons for this framework for immigration policy and the implications for R&D and education policies.

## 5.1 Tax Policy

To understand the effects of taxes on innovative output, I take the later period distribution of skills and team composition and ask how taxes affect team composition. One advantage of this framework is it allows researchers to isolate the *sorting* channel in understanding how taxation affects innovation. The counterfactual sorting from taxation comes from equalizing the returns across teams (e.g., 100% taxation does not incentivize inventors to find the "best" team, in the output sense). I focus on a tax that hits wages initially, such that for team $k$ skill $x$,

$$w'_{x,k} = (1 - \tau) w_{x,k}.$$

Because there is no endogenous aggregate labor supply in this model, the shifts in taxes shift the distribution of teams. When individuals choose teams, they now weigh the overall return to each team. Large taxes induce more "random" team matching, since individuals are more indifferent between teams. For instance, a 100% taxation leads to a fully random distribution of teams in proportion to the supply of expertise in the economy. I return to the matching equation to explore the effects of these taxes on wages. This taxes the *net* return to each team, which induces the following matching pattern:

$$\sum_{x\in k} \log\left(\frac{m_k}{m^x_{\underline{k}}}\right) = \frac{(1-\tau)\left(q_k - \sum_{x\in k} q_{\underline{k}}(x) - c_k\right)}{\phi} \qquad \text{s.t.} \qquad \sum_{k\in K(x} m_k = M_x.$$

Where aggregate innovation is $Q = \sum_{k\in\mathcal{T}} m_k q_k$. Taxes attenuate the sorting of individuals to teams. To see the quantitative results of this policy, I input 10%, 20%, and 50% taxes into the existing pattern of matches and output measures from the 1990s period. Table 3 shows the allocation of individuals to teams based on these taxes. It is not surprising that the taxes induce lower innovation. Yet a key element to note is that this tax is a wedge on the matching pattern and does not incorporate endogenous labor supply, which is a key driver in previous papers on taxation and innovation (Akcigit et al., 2016; Jaimovich and Rebelo, 2017). Further, this approach allows for more detailed counterfactual analysis of tax policy, which is of rising interest amongst economists studying innovation (Akcigit and Stantcheva, 2020; Akcigit et al., 2021).

Table 3: Taxes and Aggregate Innovation

| **Tax rate** | **Aggregate innovation** | **% change from baseline** |
|---|---|---|
| 0% | 1 | 0 |
| 10% | 0.93 | -7% |
| 20% | 0.86 | -14% |
| 50% | 0.64 | -36% |

*Notes:* This table compares the aggregate innovation from the matching pattern and idea production with different levels of taxes. Rows 2–4 introduce taxes into the matching model and ask about the counterfactual allocation and corresponding innovative output. Source: USPTO, FIPS, and author calculations.

Table 3 expresses a simple result. The changes in tax policy indicate that, to understand the effects of taxes, policymakers should think through the sorting of individuals to teams. This is an element that must be kept in mind for policymakers interested in raising revenue through taxing inventors.

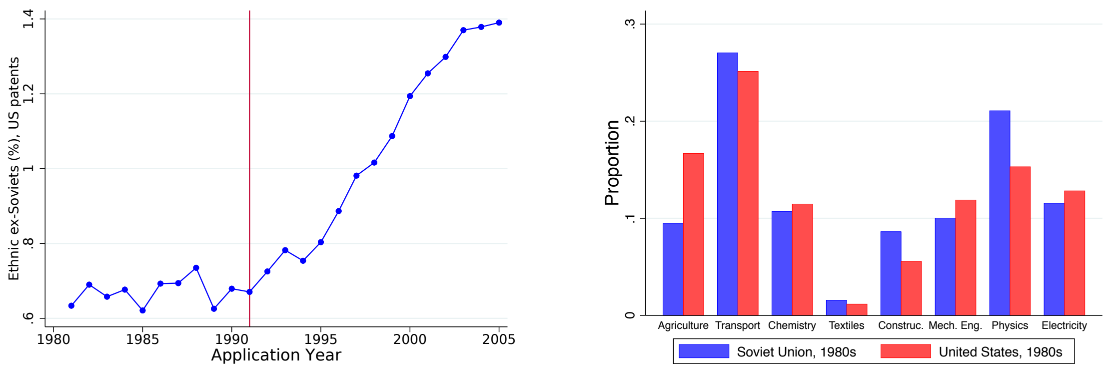
There are many possible additions to this policy. It is possible individuals have interest in sorting to higher productivity teams for reasons other than the private return. This would attenuate the result, thus it is reasonable to think of this result as an upper bound of the effect on sorting if preferences are positively correlated with output (e.g., people prefer the more productive team regardless). Going in the other direction, high enough taxes may may reduce the labor supply of inventors. Both avenues are important to observe to correctly characterize the effects of taxes on innovation. I now turn to a real-world immigration shock to learn more general lessons about migration and innovation.

## 5.2 Real-World Immigration Shock

Inventors often move across borders, and immigration policies can have a significant impact on the global distribution of talent (Akcigit et al., 2016; Kerr, 2018). Recent studies (such as Burchardi et al., 2020 and Prato, 2022) find significant effects of immigrants on innovation. Prato (2022) points out the co-author spillovers with current or prior teamwork from this channel. This section applies a key point in this paper to build a bridge to this literature. To understand the contribution of immigrants, it is essential to understand that immigrant inventors are self-selected, and selection is in large part determined by opportunities in teams and the value of having a given expertise in a given economy.

To understand immigration through the lens of specific expertise and team production, I use a historical episode and new data from the Soviet Union. After the fall of the Soviet Union, there was a large influx of Russian inventors into the US. Figure 3a plots the proportion of Russians on US patents in the 1980s and the sudden uptick post-1991 when the Soviet Union fell. Figure 3b shows the differential expertise of the US and the Soviet Union in the 1980s. This figure provides a promising example of a talent supply shock (as seen in Figure 3a) of different types of inventors (in Soviet Union versus US as in Figure 3b).

Figure 3: Fall of the Soviet Union




(a) Ethnic Russians on US patents

(b) Soviet and US tech production, 1980s

*Notes:* Panel (a) plots the share of ex-Soviet bloc ethnicities on US patents in the USPTO. Panel (b) shows the technological distribution of patents in the Soviet Union compared to patents in the US in the 1980s by IPC1 technology category. Source: USPTO, FIPS and Kerr (2007).

I use this shock to validate elements of the model and provide suggestive implications for immigration policies, in a similar manner to previous work studying the impact of Russian mathematicians on the west (Borjas and Doran, 2012; Agrawal et al., 2016). I start by shocking the distribution of expertise in the US economy in the 1990s in proportion to the amount of newly arrived Russians from 1995–2005 (as seen in Figure 3a) with the corresponding predicted expertise (Figure 3b). This delivers the projected aggregate innovation of an increase in the supply of Russians by 0.7% of the US population, which captures their expertise from the Soviet Union.[13]

I compare the predicted and realized contribution of immigrating Russians using patents from newly arrived ethnic Russians in USPTO data. In this exercise, I remove the existing set of Russians with their expertise and project the counterfactual aggregate innovation. For both these exercises, it is crucial to define aggregate innovation,

[13] I abstract away from the spatial distribution of inventors for this exercise and focus only on the expertise.

$$Q = \sum_{k \in \mathcal{T}} m_k q_k.$$

Understanding matching of team types, $m_k$, and idea production, $q_k$, allows me to study of different distributions of expertise in the economy and their contribution to aggregate innovation. After studying the response of the economy to the Russian influx, I turn to general principles that provide qualitative insights for economic policy.

To identify USPTO inventors who are Russian, I link ethnicity probabilities to inventors in the US using a procedure from Kerr (2007). I classify an inventor as a certain ethnicity if their name delivers a greater than 0.5 probability of the given ethnicity through first and last name match. In addressing how Russian expertise contributed to US innovation, I compare the distribution of the Soviet Union across IPC3 patent classes to the US distribution across IPC3 classes in the 1980s. I perform the same comparison with ethnic Russians in the US from 1995–2005, whose first patent was produced after 1991. There is no way to match specific names from the Soviet Union to the US given the common name changes that took place as Russians moved. To specify the probable immigrants, I use the ethnicity of "new" patenters of Russian ethnicity to infer whether they are from the Soviet Union.

As Borjas (1987) notes, immigrants to the United States are self-selected. I model this through a moving cost $\psi$ that each immigrant faces. This cost will induce selection for immigrants associated with skills that have more value in the US. Since Proposition 2 delivered a rank order of the value of expertise, I leverage this to generate the private value in the US of being a specific type of inventor. Those with expertise in low value patent classes may not find it worth it to move given the small change in returns by moving to the US. Equation (8) returns to this result,

$$\mathbb{E}[V_x] = cons + \underbrace{q_{\underline{k}}(x)/\phi}_{\text{value alone}} + \underbrace{\log\left(\frac{M_x}{m_{\underline{k}}^x}\right)}_{\text{value from teams}} - \underbrace{\psi}_{\text{moving cost}}. \tag{8}$$

Due to the moving cost being unobserved, I explore different implied $\psi$ cutoffs. When presenting the impact of Russian migrants, I focus on different implicit moving costs that would tend to draw high types as in Equation (8). Due to the flat returns to innovation in post Soviet Russia, it is sensible that those with higher value technologies in the US would be more likely to migrate. I confirm this by asking how correlated the predicted distribution of Russians across patent classes is to the realized distribution.

Table 4 compares the two exercises and their correlation. Panel A shows the contribution of Russians to aggregate innovation predicted by the Soviet Union records with varying degrees of self-selection. The third column compares the predicted distribution of experts to the realized distribution. For the predicted change using Soviet data, I show how the output response changes depending on the degree of self-selection (no self-selection, and the top 50 and 20 IPC3 classes as cutoffs respectively). Panel B delivers the model-implied realized contribution of newly arrived Russians in teams. Note this value is closer to the predicted value with significant self-selection.

Table 4: Contribution to Aggregate Innovation, 1995–2005

| **Measure** | **Δ Agg. Innov (%)** | ***Corr(Pred. SU, RU in US)*** |
|---|---|---|
| *— Panel A. Predicted Impact, Soviet Union shock —* | | |
| No selection | 0.55 | 0.69 |
| Selection at T50 | 0.77 | 0.86 |
| Selection at T20 | 1.08 | 0.88 |
| *— Panel B. Realized Impact of Soviet Union shock —* | | |
| Russian inflow | 0.81 | 1 |

*Notes:* Calibrated model output using counterfactual skill distribution. In Panel A, each row represents a simulated distribution of teams adding the shock from the Soviet talent, with different selection thresholds (e.g. proportional to selection) from Equation (8). In Panel B, the actual Russian distribution is simulated. Source: USPTO, FIPS and author calculations.

I stress two main results from Table 4. First, the Russian contribution to aggregate innovation was 15% greater than their increase in the population in terms of inventors (0.81 vs. 0.70). Second, this was due to the self-selection of Russian migrants, which is a key element of migration generally; individuals migrate depending on the available teams and impact of producing alone (almost 90% of Russians produced in teams). If the US distribution were shocked with the same mass of new inventors distributed as in the Soviet Union, it would understate the Russian contribution significantly (0.55 vs. 0.81). This result is robust to different skill measures and output measures, as discussed in Section 6 and Appendix C.1. To understand the role of immigration in this setting, researchers and policymakers must consider the distribution in the Soviet Union, the degree of self-selection, and the team contribution channel. This paper provides a quantitative framework for this analysis.

This result contains more general lessons for policymakers who want to leverage immigration to increase innovation. First, a general increase in high-skilled immigration will tend to contribute more than purely predicted through the skill distributions due to self-selection. Second, for targeted policies, there are simple statistics that can help policymakers understand the skills most in demand. If policymakers want to target specific skills, they can leverage Proposition 2 and Equation (8). This provides a framework to rank skills by their predicted impact. This is because the private value of having a given skill in a team economy is highly correlated with public value.[14] Policymakers with incomplete information about the structure of the innovation economy can rely on two straightforward pieces of information from Equation (8): how productive is a specific inventor type (e.g. organic chemist) alone, and how often are they in teams? The impact of a given expertise will be increasing in both of these observed outcomes.

# 6 Discussion and Robustness

The quantitative results developed in Section 4 and Section 5 deliver the baseline results in this paper on the sources and implications of the rise in teams. The results are based on the empirical measures discussed in Section 3. To ensure that my results are robust, this section provides reduced-form evidence on the quantitative mechanism, discusses the

[14] Appendix C discusses these issues in greater detail.

measure of communication costs, and explores the robustness of results to different measures of patent quality and domain expertise. In Appendix D, I vary measures of inputs and outputs, changing the time window, and changing the geographical distance measure.

## 6.1 Testing the Quantitative Mechanism

The quantitative analysis indicated that the rising benefits of working in teams relative to working alone is the most prevalent force driving the change in team size, yet communication costs also played an important role. The decomposition quantifies each role, but I did not directly focus on how production changed.

This section focuses on some reduced form empirical results to test the overall quantitative mechanism. In Appendix B, I focus on the *costs* of forming teams and the compositional effects in a reduced form way. I start by characterizing the returns to depth and breadth in the 1980s and the 1990s, to focus on the impact of patents depending on the skill-set of individuals on the team.

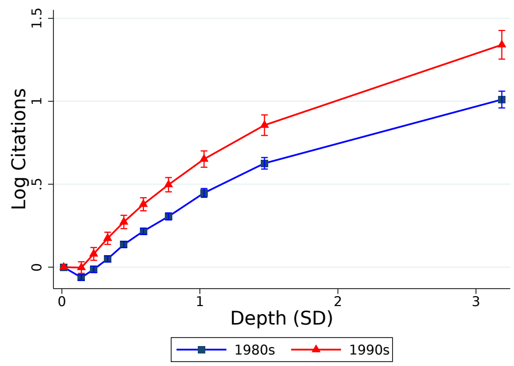
Teams with more depth and breadth produce more impactful patents, and even more so in the 1990s than in the 1980s. To evaluate the regression with depth and breadth as the driving force behind production, I take log citations as the $y$-variable, exploring other variables in Appendix D.[15] As inputs, I take the depth and breadth at the patent-team level and build deciles of each over time. Equation (9) illustrates the specification:

$$y_{p(k,s)} = \alpha_0 + \sum_{j=2}^{10} \alpha_j \mathbb{I}\{Decile(D_{k,s}) = j\} \times 1990s + \sum_{i=1}^{10} \zeta_j \mathbb{I}\{Decile(B_{k,s}) = j\} \times 1990s + \mathbf{Z}_{p(k,s)} + u_p. \tag{9}$$

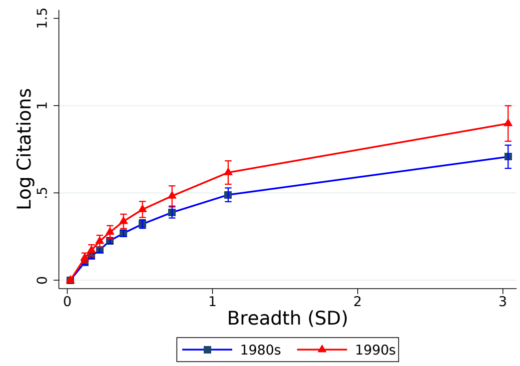
Equation (9) includes an interaction term for the 1990s. The goal is to outline how log citations respond to depth and breadth across the two different time periods. If there were a change to the idea production function over time, then one would expect higher coefficients on depth and breadth in the 1990s relative to the 1980s.

[15] To be consistent with the literature and account for zeroes, I take the inverse hyperbolic sine transform. However, this result looks similar with dropping zeroes.

Figure 4: Citations and Depth/Breadth, 1980s versus 1990s




(a) Depth




(b) Breadth

*Notes:* This figure plots the coefficients from Equation (9) split by time period. Skills are accumulated from all time periods for analysis, but the regressions only include lifetime citations from 1980–2000. Source: USPTO and author calculations.

As indicated in Figure 4, higher-decile depth and breadth are linked to higher-quality patents in the later period. These results illustrate that the returns to skill are changing over time, as patents exhibit a stronger response to team depth and breadth. This is true even when controlling for team size, technology, and year effects. It also holds when building quintiles by period. These results, with the relatively higher impact of more breadth and depth, are consistent with the findings in Section 4. One concern is that the communication costs could shift not just the propensity to find teams but also the *quality* of output. I find that this regression looks similar for both individuals in the same location and individuals working at a distance.

This section characterizes the gross output measures for various collections of expertise of teams, $q_k$. I show in Appendix B that locational distance has negligible effects on patent quality, so the main focus on the benefits of teams is through expertise, though I leave a discussion to endogenous location sorting for later research.

**Communication Costs.** In the main quantitative section of this paper, I treat the unexplained aspect of the rise of teams as a residual due to falling communication costs. It is possible this overstates the role of communication costs, as it assigns all team formation not due to the observed composition and returns to communication costs. In Appendix D, I discuss a model where I focus on the locational distribution of inventors and find that increased communication at a distance can explain 25% of the rise in team size from the 1980s to the 1990s. This does not focus on communication costs that make communicating within the same geographical region (e.g., less than 100 miles distance) easier.

As a result, it is safe to say that falling communication costs should at least contribute 25% to the rise of team size from 1980s to 1990s, and at most contributes to 41% of the rise. Thus, communication costs are a significant force behind the rise of teams, and suggest a benign interpretation of this rise. However, the changing nature of ideas appears to be stronger in driving the rise of teams.

# 7 Conclusion

Complex tasks in the economy increasingly require more varied skills and larger teams; this is particularly salient in the case of innovation. This paper addresses the forces that underlie the increasing importance of teams in innovation as well as their macroeconomic and policy implications by building a quantitative framework of matching and innovation in teams.

I build a team idea production and matching framework. With this framework and USPTO patent data, I quantify the role that three major forces play in driving these patterns: benefits (the idea production function), costs (communication costs), and supply (inventor expertise composition). I find that all three forces are relevant for both the technological composition of the economy and the prevailing team size; changes in the idea production function, as understood through the returns to teams, explain most of the change in team size.

Given the rising importance of fostering complementary skills, the results have relevant policy implications. The model provides immediate insights on both taxation and immigration policy. For taxation, the interaction of taxes with sorting into teams has first-order effects on aggregate innovation. For immigration, the model provides a good basis for policymakers interested in skills-based innovation policy and a method for modeling how self-selection of immigrants interacts with overall innovation.

This framework suggests further avenues to explore. For instance, while this model delivers a distribution of expected values across expertise, the cost of training each of domain of expertise is important to know for questions of skill investment and education policy. Understanding the interaction of the cost of training skills and the innovative output is a fruitful area for research. Lastly, this paper provides a promising framework to understand the incentives of firms to collect teams and the interaction of firm dynamics with team dynamics. Thus, this paper can serve as a first step to quantify the rise of teams in innovation and provide a framework for a broad range of investigations into how teams interact with economic growth.

# References

Adams, J. D., G. C. Black, J. R. Clemmons, and P. E. Stephan: 2005, 'Scientific teams and institutional collaborations: Evidence from U.S. universities, 1981-1999'. *Research Policy* **34**(3), 259 – 285. University-based Technology Initiatives.

Aghion, P. and P. Howitt: 1992, 'A Model of Growth Through Creative Destruction'. *Econometrica* **60**(3), 323–351.

Agrawal, A. and A. Goldfarb: 2008, 'Restructuring Research: Communication Costs and the Democratization of University Innovation'. *American Economic Review* **98**(4), 1578–90.

Agrawal, A., A. Goldfarb, and F. Teodoridis: 2016, 'Understanding the Changing Structure of Scientific Inquiry'. *American Economic Journal: Applied Economics* **8**(1), 100–128.

Akcigit, U., S. Baslandze, and S. Stantcheva: 2016, 'Taxation and the International Mobility of Inventors'. *American Economic Review* **106**(10), 2930–81.

Akcigit, U., S. Caicedo, E. Miguelez, S. Stantcheva, and V. Sterzi: 2018, 'Dancing with the Stars: Innovation Through Interactions'. Working Paper 24466, National Bureau of Economic Research.

Akcigit, U., J. Grigsby, and T. Nicholas: 2017, 'Immigration and the Rise of American Ingenuity'. *American Economic Review* **107**(5), 327–31.

Akcigit, U., J. Grigsby, T. Nicholas, and S. Stantcheva: 2021, 'Taxation and Innovation in the Twentieth Century*'. *The Quarterly Journal of Economics* **137**(1), 329–385.

Akcigit, U., B. Kerr, T. Nicholas, and J. Pearce: 2022, 'The Mechanics of Endogenous Innovation and Growth: Evidence from Historical US Patents'. Working paper.

Akcigit, U., J. G. Pearce, and M. Prato: 2020, 'Tapping into Talent: Coupling Education and Innovation Policies for Economic Growth'. Working Paper 27862, National Bureau of Economic Research.

Akcigit, U. and S. Stantcheva: 2020, 'Taxation and Innovation: What Do We Know?'. Working Paper 27109, National Bureau of Economic Research.

Alchian, A. A. and H. Demsetz: 1972, 'Production, Information Costs, and Economic Organization'. *The American Economic Review* **62**(5), 777–795.

Azoulay, P., J. S. Graff Zivin, and J. Wang: 2010, 'Superstar Extinction'. *Quarterly Journal of Economics* **125**(2), 549–589.

Becker, G. and K. M. Murphy: 1992, 'The Division of Labor, Coordination Costs, and Knowledge'. *Quarterly Journal of Economics* **107**(4), 1137–1160.

Becker, G. S.: 1973, 'A Theory of Marriage: Part I'. *Journal of Political Economy* **81**(4), 813–846.

Bennett, L. M. and H. Gadlin: 2012, 'Collaboration and team science: from theory to practice'. *Journal of Investigative Medicine* **60**(5), 768–775.

Berkes, E. and R. Gaetani: 2019, 'The Geography of Unconventional Innovation'. Working Paper 3423143, Rotman School of Management Working Paper.

Bikard, M., F. Murray, and J. S. Gans: 2015, 'Exploring Trade-offs in the Organization of Scientific Work: Collaboration and Scientific Reward'. *Management Science* **61**(7), 1473–1495.

Bloom, N., C. I. Jones, J. Van Reenen, and M. Webb: 2020, 'Are Ideas Getting Harder to Find?'. *American Economic Review* **110**(4), 1104–44.

Borjas, G. J.: 1987, 'Self-Selection and the Earnings of Immigrants'. *American Economic Review* **77**(4), 531–553.

Borjas, G. J. and K. B. Doran: 2012, 'The Collapse of the Soviet Union and the Productivity of American Mathematicians*'. *Quarterly Journal of Economics* **127**(3), 1143–1203.

Burchardi, K. B., T. Chaney, T. A. Hassan, L. Tarquinio, and S. J. Terry: 2020, 'Immigration, Innovation, and Growth'. Working Paper 27075, National Bureau of Economic Research.

Choo, E. and A. Siow: 2006, 'Who Marries Whom and Why'. *Journal of Political Economy* **114**(1), 175–201.

Falk-Krzesinski, H. J., K. Borner, N. Contractor, S. M. Fiore, K. L. Hall, J. Keyton, B. Spring, D. Stokols, W. Trochim, and B. Uzzi: 2010, 'Advancing the Science of Team Science'. *Clinical and Translational Science* **3**(5), 263–266.

Forman, C. and N. van Zeebroeck: 2012, 'From Wires to Partners: How the Internet Has Fostered R&D Collaborations Within Firms'. *Management Science* **58**(8), 1549–1568.

Freeman, R. and W. Huang: 2015, 'Collaborating with People Like Me: Ethnic Coauthorship within the United States'. *Journal of Labor Economics* **33**(S1), S289 – S318.

Garicano, L. and E. Rossi-Hansberg: 2006, 'Organization and Inequality in a Knowledge Economy'. *The Quarterly Journal of Economics* **121**(4), 1383–1435.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg: 2001, 'The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools'. *National Bureau of Economic Research Working Paper no:8498*.

Hayek, F. A.: 1945, 'The Use of Knowledge in Society'. *The American Economic Review* **35**(4), 519–530.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow: 2019, 'The Allocation of Talent and U.S. Economic Growth'. *Econometrica* **87**(5), 1439–1474.

Hunt, J. and M. Gauthier-Loiselle: 2010, 'How Much Does Immigration Boost Innovation?'. *American Economic Journal: Macroeconomics* **2**(2), 31–56.

Jaimovich, N. and S. Rebelo: 2017, 'Nonlinear Effects of Taxation on Growth'. *Journal of Political Economy* **125**(1), 265–291.

Jaravel, X., N. Petkova, and A. Bell: 2018, 'Team-Specific Capital and Innovation'. *American Economic Review* **108**, 1034–1073.

Jones, B. F.: 2009, 'The Burden of Knowledge and the "Death of the Renaissance Man" Is Innovation Getting Harder?'. *The Review of Economic Studies* **76**(1), 283–317.

Jones, C. and J. Williams: 1998, 'Measuring the Social Return to R&D'. *The Quarterly Journal of Economics* **113**(4), 1119–1135.

Jones, C. I.: 1995, 'R&D-Based Models of Economic Growth'. *Journal of Political Economy* **103**(4), 759–84.

Jones, C. I.: 2005, 'Growth and Ideas'. Vol. 1 of *Handbook of Economic Growth*. Elsevier, pp. 1063 – 1111.

Jones, C. I.: 2021, ‘Recipes and Economic Growth: A Combinatorial March Down an Exponential Tail’. Working Paper 28340, National Bureau of Economic Research.

Jones, C. I.: 2022, ‘Taxing Top Incomes in a World of Ideas’. *Journal of Political Economy* **130**(9), 2227–2274.

Kerr, W. and W. Lincoln: 2010, ‘The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention’. *Journal of Labor Economics* **28**(3), 473–508.

Kerr, W. R.: 2007, ‘The Ethnic Composition of US Inventors’. Harvard Business School Working Papers 08-006, Harvard Business School.

Kerr, W. R.: 2018, *The Gift of Global Talent*. Stanford University Press.

Kim, E. H., A. Morse, and L. Zingales: 2009, ‘Are elite universities losing their competitive edge?’. *Journal of Financial Economics* **93**(3), 353–381.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman: 2017, ‘Technological Innovation, Resource Allocation, and Growth’. *The Quarterly Journal of Economics* **132**(2), 665–712.

Kortum, S.: 1997, ‘Research, Patenting, and Technological Change’. *Econometrica* **65**(6), 1389—1419.

Li, G.-C., R. Lai, A. D’Amour, D. M. Doolin, Y. Sun, V. I. Torvik, A. Z. Yu, and L. Fleming: 2014, ‘Disambiguation and co-authorship networks of the U.S. patent inventor database (1975-2010)’. *Research Policy* **43**(6), 941 – 955.

Lucas, R. E.: 1988, ‘On the Mechanics of Economic Development’. *Journal of Monetary Economics* **22**(1), 3 – 42.

Lucas, R. E.: 2009, ‘Ideas and Growth’. *Economica* **76**(301), 1–19.

Lucas, R. E. and B. Moll: 2014, ‘Knowledge Growth and the Allocation of Time’. *Journal of Political Economy* **122**(1), 1—51.

Marschak, J. and R. Radner: 1972, *Economic theory of teams*. Yale University Press.

McFadden, D.: 1974, 'Conditional Logit Analysis of Qualitative Choice Behavior,'. Frontiers in Economics, Chapter 4, ed. d. by P. Zarembka, New York: Academic Press.

Moser, P., A. Voena, and F. Waldinger: 2014, 'German Jewish Emigres and US Invention'. *American Economic Review* **104**(10), 3222–55.

Perla, J. and C. Tonetti: 2014, 'Equilibrium Imitation and Growth'. *Journal of Political Economy* **122**(1), 52—76.

Prato, M.: 2022, 'The Global Race for Talent: Brain Drain, Knowledge Transfer, and Growth'. SSRN Working Paper 4287268.

Romer, P.: 1990, 'Endogenous Technological Change'. *Journal of Political Economy* **98**(5), S71–102.

Stokey, N. L.: 2018, 'Technology, Skill, and the Wage Structure'. *Journal of Human Capital* **12**(2), 343–384.

Tao, T.: 2017, 'Australian Spotlight Interview, minute 20:55'.

Teodoridis, F.: 2018, 'Understanding Team Knowledge Production: The Interrelated Roles of Technology and Expertise'. *Management Science* **64**(8), 3625–3648.

Weitzman, M. L.: 1998, 'Recombinant Growth'. *Quarterly Journal of Economics* **113**(2), 331–360.

Wuchty, S., B. F. Jones, and B. Uzzi: 2007, 'The Increasing Dominance of Teams in Production of Knowledge'. *Science* **316**(5827), 1036–1039.

# Online Appendix

The Appendix is in four sections. Appendix A discusses the data background and general points about large firms and brand acquisitions. Appendix B discusses the empirical analysis connections to the literature and robustness. Appendix C discusses the counterfactuals in greater detail. Appendix D discusses the robustness of the empirical and quantitative results.[16]

## A Theoretical Appendix

This theoretical appendix contains proofs of Proposition 1 and Proposition 2.

### A.1 Proposition Proofs

**Proof of Proposition 1**

*Proof.* I ensure there exists an equilibrium that satisfies the 5 conditions set out in the equilibrium definition in Section 2. For notational purposes, I treat distinct types of skills $x$ and discard location for notational purposes.

The mass of type $x$ that is assigned to team $k$ follows from the mass $M_x$ multiplied by the probability a type $x$ goes to team $k$. Following McFadden (1974), I show how I derive this probability given the set of sharing rules.

$$Pr\{k_x^*(i) = k\} = Pr(w_k^x + \epsilon_k^x(i) > w_{\tilde{k}}^x + \epsilon_{\tilde{k}}^x(i) \ \ \forall \ \ \tilde{k} \neq k)$$

I take individuals' shocks across all teams $k$ as $F(\epsilon) = \exp(\exp(-\epsilon/\phi))$. Then, with utility from team $k$ as follows:

$$\pi_k^x(i) = w_k^x + \epsilon_k^x(i)$$

[16] For notes discussing additional details and facts, please see https://www.jeremygpearce.com/IPTS_teams.

The probability individual $i \in x$ chooses team $k$ is:

$$\mathbb{P}\{\epsilon^x_{\tilde{k}}(i) < w^x_k - w^x_{\tilde{k}} + \epsilon^x_k(i)\ \forall\ \tilde{k} \neq k\}$$

$$= \int_{-\infty}^{\infty} \prod_{k \neq k} F(w^n_k - w^n_{\tilde{k}} + \epsilon^n_k) f(\epsilon^n_k) d\epsilon^n_k$$

Plug in the distribution of the shocks

$$= \int_{-\infty}^{\infty} \prod_{\tilde{k} \neq k} \exp\{-\exp[-(w^x_k - w^x_{\tilde{k}} + \epsilon^x_k)]\} \exp[-\epsilon^x_k - \exp(\epsilon^x_k)] d\epsilon^x_k$$

I perform a change of variable to generate $\psi = \exp(-\epsilon^x_{\tilde{k}})$ and $z_{\tilde{k}} = \exp[-(w^x_k - w^x_{\tilde{k}})]$. then:

$$\mathbb{P}(k^* = k) = \int_0^{\infty} \exp\left[\psi\left(1 + \sum_{\tilde{k} \neq k} z_{\tilde{k}}\right)\right] d\psi = \frac{1}{1 + \sum_{\tilde{k} \neq k} z_{\tilde{k}}} = \frac{\exp(w^n_k / \phi)}{\sum_{\tilde{k} \in \mathcal{T}_n} \exp(w^n_{\tilde{k}} / \phi)}$$

Optimization leads us to the assignment to team $k$ as follows:

$$m^x_k = M_x \cdot \frac{\exp M_x(w^x_k / \phi)}{\sum_{\tilde{k} \in \mathcal{T}_x} \exp(w^x_{\tilde{k}} / \phi)} \tag{10}$$

I use the knowledge of the value of working alone ($q_{\underline{k}}(x)$):

$$m_{\underline{k}} = M_x \frac{\exp(q_{\underline{k}}(x) / \phi)}{\sum_{\tilde{k} \in \mathcal{T}_x} \exp(w^x_{\tilde{k}} / \phi)}$$

as well as the market clearing condition in teams,

$$m^x_k = m_k$$

To simplify Equation (10) as follows:

$$\log m_k - \log \frac{m_{\underline{k}}}{N_k^x} = \frac{w_k^x - q_{\underline{k}}(x)}{\phi}$$

Finally, I use Equation (E2) ($\sum_k w_k^{x'} = q_k - c_k$) to sum up this equation across each agent in the team, to get:

$$\log m_k - \frac{1}{T} \sum_{x \in k} \log \frac{m_{\underline{k}}}{N_k^x} = \frac{q_k - \sum_{x \in k} q_{\underline{k}}(x) - c_k}{\phi T_k}$$

Satisfying (E1)-(E5) delivers an allocation and set of sharing rules that confirms the proposition.

□

**Proof of Proposition 2**

*Proof.* Conditional on an agent $i \in x$ choosing a team $k$, the expected utility of this agent is:

$$\begin{aligned}
\mathbb{E}\left[\pi_k^x | k = \arg\max_{k' \in \mathcal{T}_x} \pi_{k'}^x\right] &= w_k^x + \mathbb{E}\left[\epsilon_k^x(i) \middle| w_k^x + \epsilon_k^x(i) > w_{\tilde{k}}^x + \epsilon_{\tilde{k}}^x(i)\ \forall\ \tilde{k} \neq k\right] \\
&= w_k^x + \mathbb{P}\left[\pi_k^x \middle| k = \arg\max_{k' \in \mathcal{T}_x} \pi_{k'}^x\right]^{-1} \times \\
&\int_{-\infty}^{\infty} \epsilon_k^x(i) \exp\left[-\epsilon_k^x(i) - e^{-\epsilon_k^x(i)}\left(1 + \sum_{\tilde{k} \neq k} \eta_{\tilde{k}}\right)\right] d\epsilon_k^x(i)
\end{aligned}$$

Where I define $\eta_{\tilde{k}} \equiv \exp\left[-\left(\epsilon_k^x(i) - \epsilon_{\tilde{k}}^x(i)\right)\right]$ The result above is standard and comes from the assumption on the distribution of the shocks across teams. I now use a standard result from math, which shows that $\int_{-\infty}^{\infty} x \exp(x - \eta e^x) dx = -(c + \log \eta)/\eta$ with $c$ as Euler's constant. This delivers the following equation:

$$\mathbb{E}\left[\pi_k^x | k = \arg\max_{k' \in \mathcal{T}_x} \pi_{k'}^x\right] = c + \log\left(\sum_{\tilde{k} \in \mathcal{T}_x} \exp(w_{\tilde{k}}^x / \phi)\right) \tag{11}$$

Note this equation is independent of the specific team $k$, and only depends on the distribution of potential teams for the given inventor. I unite this equation with the equation that governs the demand equation for type $x$ as a sole inventor:

$$m^x_{\underline{k}} = M_x \frac{\exp(q_{\underline{k}}(x)/\phi)}{\sum_{\tilde{k}\in\mathcal{T}_x}\exp(w^x_{\tilde{k}}/\phi)}$$

$$\mathbb{E}\left[\pi^x_k | k = \arg\max_{k'\in\mathcal{T}_x}\pi^x_{k'}\right] = c + \log\left(\frac{M_x}{m^x_{\underline{k}}}\exp(q_{\underline{k}}(x)/\phi)\right) = c + \log\frac{M_x}{m^x_{\underline{k}}} + q_{\underline{k}}(x)/\phi \tag{12}$$

This delivers our result:

$$\mathbb{E}[V_x] \propto cons + \underbrace{q_{\underline{k}}(x)}_{\text{output alone}} + \underbrace{\phi\log\left(\frac{M_x}{m^x_{\underline{k}}}\right)}_{\text{concentration in teams}} \tag{13}$$

□

# B Empirical Appendix

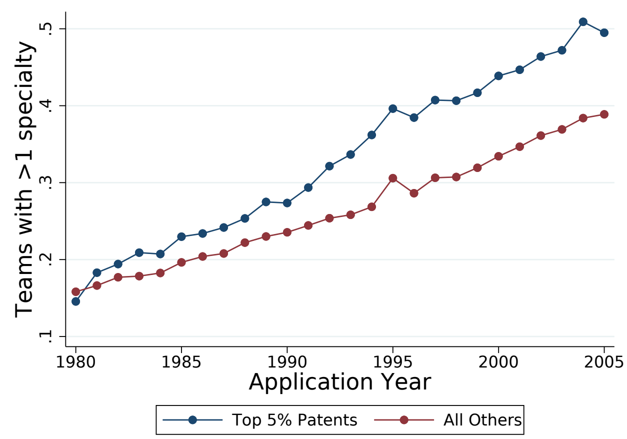
This section complements the main text by including more general indicating of rising diversity across teams. This result is consistent with the rising diversity of expertise in teams.

## B.1 Rising Diversity

In the introduction, I discussed the rise in team diversity in terms of differentiated expertise. Here, I document three facts that are indicative of this rising diversity. While some background characteristics (e.g., gender and ethnicity) are not relevant for economic output, scholars have noted the link between background diversity and cognitive diversity and found that more diverse teams ethnically produce higher impact patents (see Freeman and Huang, 2015).

I show three graphs that depict the rise in diversity in teams. First, note the rising trend of inventors collaborating together who started in different fields. Figure B.1 illustrates the proportion of patents that have at least two inventors whose initial patent was different from the other inventor. Further, it suggests these are the higher impact patents especially that are being assigned to the diverse teams:

Figure B.1: Prop. patents with $\geq 2$ unique technological backgrounds




Next, I turn to ethnic diversity. Figure B.2 takes the same ethnic measures as Kerr (2007) and asks how many patents have two distinct ethnicities, and shows that this has been rising steadily over time, more than doubling as a proportion of total patents from 1985–2005.

Lastly, I note that teams of males and females working together is on the rise, with names probabilistically matched to genders in Figure B.3. I note the rise in teams with two different gender, which almost doubles from 1985–2005.

## B.2 Classification Example: IPC3

This paper uses both USPTO and IPC classifications. Both are standard in the patent literature. In order to match the data to records from the Soviet Union, I exploit IPC classification for the quantitative exercise, both at the 2-digit and 3-digit IPC level. Figure B.4 details examples of different layers of classification from IPC1 to IPC3.

Figure B.2: Prop. 2-person team patents with $\geq$ 2 unique ethnic backgrounds

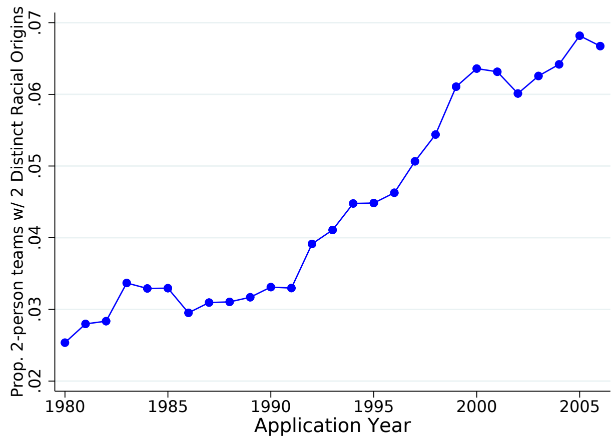
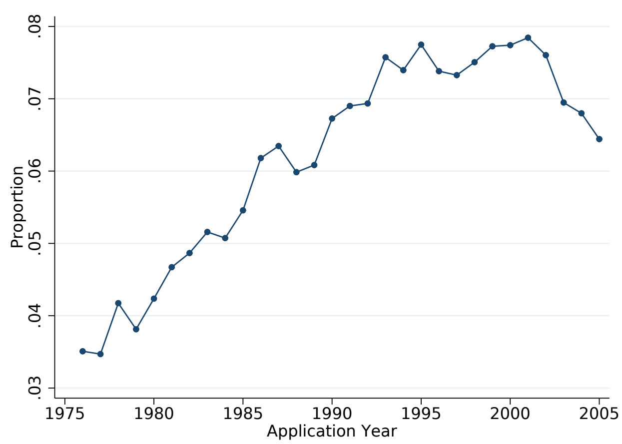



Figure B.3: Proportion of teams with male+female




## B.3 Unique Inventors and Unique Patents

For one robustness, I focus on individuals who work on sole-authored patents to ensure the domain of expertise in well-identified (see Appendix D). Table B.1 addresses the count of individuals over time who have had at least one sole-authored patent and their average team size in the two main periods analyzed in the paper.

Figure B.4: Technology classifications (IPC)

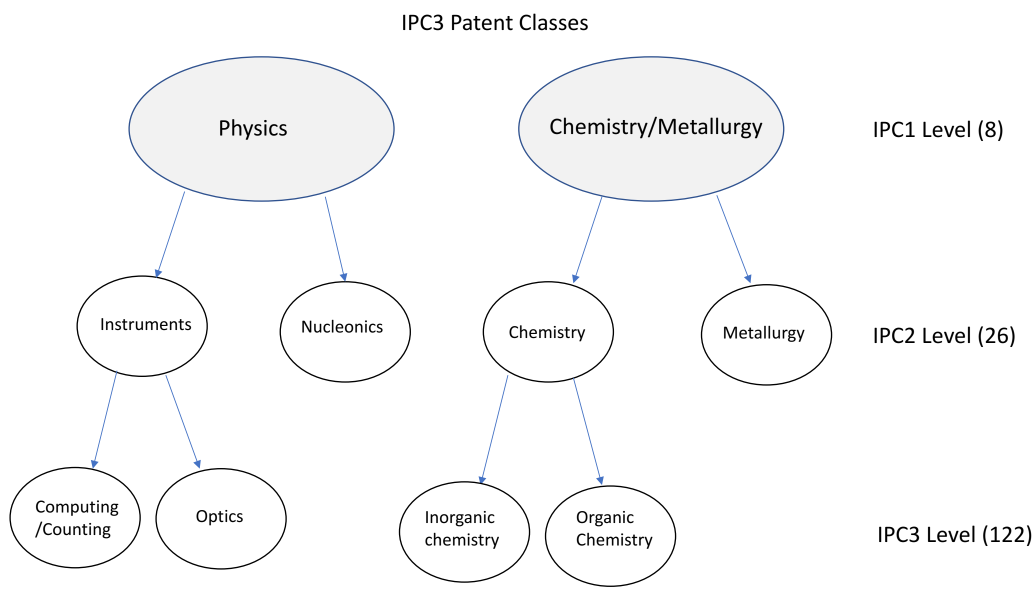



Table B.1: Counts

| Time period | Patent Count | Author Count | Avg. Team Size |
|---|---|---|---|
| 1980-1990 | 611103 | 269286 | 1.537 |
| 1991-2000 | 968874 | 361882 | 1.802 |
| Growth | 58.5% | 34.3% | **17.2%** |

*Notes:* Patent counts and individuals and team size by decade. Source: USPTO and author calculations

# C Policy and Immigration Application

This section addresses more details of the expertise distribution of newly arrived Russians and the robustness of the general results. Appendix C.1 discusses the application from the fall of the Soviet Union and specific technologies and the robustness of the results to changes in the categorization of team types and output measures. Appendix C.2 discusses the more general immigration policy results, the role of self-selection in migration amplifying innovation, and the general results on the economic value of specific types. Appendix C.3 discusses R&D and education policy applications. Appendix C.4 discusses the computational exercise of shocking the system.

## C.1 Soviet Union Shock

In the main text, I use IPC2 classifications for talent supply shocks. In exploring the robustness, I use a more granular definition of skills by mapping individual expertise to IPC3 classes with sufficient observations (122 unique categories). I take the individual's top category when working alone, then on teams of 2, and so on. Inventors with only one patent observation are not classified according to a type.

Figure C.5 plots the concentration of the Soviet Union and the United States across patent classes according to the IPC3 patent classifications. This figure illustrates the heterogeneous exposure across classes that enable use of the fall as a shock to the supply of talent.

Figure C.5: Concentration of US and Soviet Union across IPC3, 1980-1990

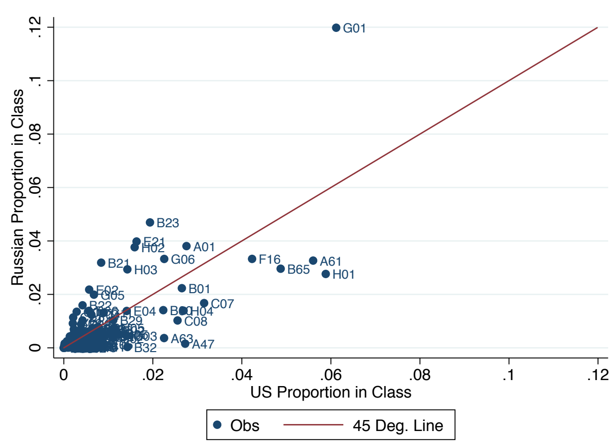
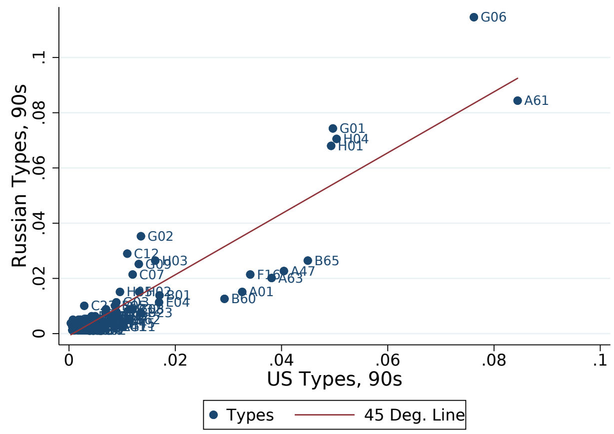



Figure C.6 illustrates that the concentration of Russians across types in the IPC3 categories has some resemblance of matching the pre period. However, there is selection in the migration pattern, as discussed in Section 5.

Figure C.6: Concentration of US and Soviet Union across IPC3, 1991-2000




Self-selection amplifies the Russian overall contribution to output. This can be observed in the main text when I use IPC2 types and teams up to size three. Here, we use teams up to size two and types by IPC3 and find similar results.

Table C.2: Contribution to Aggregate Innovation, 1995–2005

| **Measure** | **Δ Agg. Innov (%)** | ***Corr(Pred. SU, RU in US)*** |
|---|---|---|
| *— Panel A. Predicted Impact, SU shock —* | | |
| No selection | 0.56 | 0.51 |
| Selection at T50 | 0.79 | 0.62 |
| Selection at T20 | 1.07 | 0.66 |
| *— Panel B. Impact of SU shock —* | | |
| Russian inflow | 0.93 | 1 |

*Notes:* Calibrated model output using counterfactual skill distribution. In Panel A, each row represents a simulated distribution of teams adding the shock from the Soviet talent, with different selection thresholds (e.g. proportional to selection) from Equation (8). In Panel B, the actual Russian distribution is simulated.

Table 4 affirms the two main results from the inflow of Russians. First, the Russian contribution to aggregate innovation was more than their increase in the population in terms of inventors (0.93 vs. 0.8). Second, this was due to the self-selection of migrants.

Table C.3 follows from Table C.2 which uses citations, but restricts attention to patents that have an associated stock market value (Kogan et al., 2017). Note again that there is a fairly close match to the predicted and realized in-sample exercise, where the selection on the types arriving to the US shapes the overall contribution. This confirms in yet another measure the value of self-selected migration and its amplification.

Table C.3: Stock market value of migrating Russian output, 1995–2005

| **Measure** | **$\Delta$ Agg. Innov (\$)** |
|---|---|
| *— Panel A. Innovation in US —* | |
| sole-authored innovation | 10.8B |
| model predicted (incl. teams) | 33.4B |
| *— Panel B. Predicted innovation from SU-US Match —* | |
| predicted, from SU data, no selection | 26.2B |
| predicted, from SU data, selection at T50 | 32.5B |

*Notes:* Market value of patents (in sample) from 1995–2005 is 3.92T

The idea production function and communication costs push in opposite directions to impact change in aggregate innovation that results from immigrant inflows. First, an addition of a worker to a country is of higher value because of their ability to contribute to teams. This would suggest immigration policy is becoming more important and it is crucial to link immigrants into the global market. Second, because international collaboration is increasing, it is less important to bring immigrants directly into the home country. Thus, it is a quantitative question of what is the dominant force to consider when designing immigration policy. We find in the quantitative section the idea production function is the most important component driving the increase in teams. This motivates immigration policy remaining an essential component of aggregate innovation.

## C.2 General Immigration Counterfactuals

To understand both the value of specific types and the correlation between self-selection and aggregate innovation, I perform a quantitative exercise aimed at understanding the impact of each type on innovation. I increase the supply of a specific inventor type in the economy by a small amount and evaluate how this changes overall innovative output.

In these counterfactuals, I take the estimated production function from the 1990s for each $q_k$, and the supply of each type $x$, $M_x$.[17] I use IPC2 classifications to characterize the expertise of each individual. I use these classifications to match the distribution of types, $M_x$, and teams, $m_k$, and team production, $q_k$, using US data from 1991-2000. The exercise then increases each type $M_x$ by 0.01 with the total population normalized to 1.

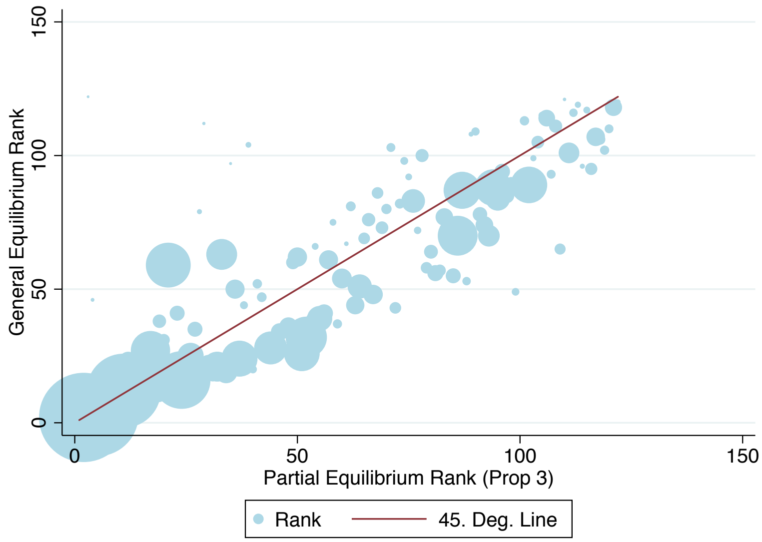
Returning to Equation (8), I compare the rank of total output generated by 1% increase in the inventor population of a specific expertise across 26 IPC3 categories to the rank from Proposition 2. Figure C.7 plots the ranks from ex ante value and ex post contribution for the 1990s time period, with the bubble size indicating the mass of each type. Notice the strong relationship between the value from Proposition 2 and the general equilibrium result of shocking the economy:

For each type, two forces – the value produced alone $q_{\underline{k}}(x)$ and the frequency that this type joins a team – are close to sufficient to characterize the outcome of increasing this specific expertise in the economy through immigration. The team element plays a key role in this value, and indicates why we see more migration from experts in Biochemistry, Organic Chemistry, and Medical Science.

I stress two takeaways from this result. First, the self-selection of immigrants has a tendency to amplify the effect of migration on innovation, as immigrants with a better fit of expertise for the society will be more likely to migrate, as was seen in the case of the Soviet Union. Second, for a policymaker whose goal is increasing aggregate innovation, there is only a limited set of information required to understand which types of expertise will make the largest contribution: the productivity of types when they work alone ($q_{\underline{k}}(x)$), their

[17] For the case of immigration inflows, I abstract away from regional communication costs within the US.

Figure C.7: Relationship between PE values and GE result




*Notes:* This figure compares ranks of IPC3 types in partial equilibrium (own marginal value) and general equilibrium (own effect on aggregate). Size of dots indicate share of individuals with given expertise.

concentration in teams, and the noise parameter, $\phi$. Even though the general equilibrium forces don't make this a perfect predictor of overall contribution, its ability to approximate the outcome can be informative for immigration policies based on skill.

Policymakers without knowledge of the noise parameter $\phi$ can rely on two straightforward pieces of information: how productive is a specific inventor type (e.g. organic chemist) alone, and how often are they in teams? Table C.4 illustrates the top expertise in the 1990s with the estimated production function.

## C.3 Discussion: R&D Subsidies and Education Policy

The team production channel induces a lot of potentially heterogeneous impact of R&D and education policy depending on its structure. The effect of R&D subsidies in this framework depend on how they target the idea market. For instance, if subsidies are directed to labs (teams), this will naturally change team composition through inducing more collaboration. Agents might be more willing to overcome communication costs in order to join teams. If

Table C.4: Ranking Types across IPC3

| | (1) | (2) | (3) |
|---|---|---|---|
| Rank (IPC3) | 1990s $E[V_x]$ rank | 1990s, alone | 1990s, in teams |
| 1 | Checking-Devices | Checking-Devices | Biochemistry |
| 2 | Medical Science | Medical Science | Organic Chemistry |
| 3 | Computing/Counting | Computing/Counting | Organic Macromolecular Compounds |
| 4 | Elec. Comm. Technique | Elec. Comm. Technique | Fatty Acids |
| 5 | Biochemistry | Signaling | Petroleum and Technical Gases |

*Notes:* Comparing ranks of top 5 IPC3 skills and indicating the relative value alone and in teams: Source: USPTO and author calculations.

a team's communication costs are borne privately while team innovative output is a public good, this could increase overall innovation. If R&D subsidies are directed towards all innovation, it will exacerbate the differences across productive and unproductive teams.

R&D subsidies would not directly hit communication costs. A subsidy on communication technology would induce more regional dispersion of teams. This is part of a natural progression, but a subsidy would induce more of this behavior. However, the R&D subsidy will hit differentially across the quality of teams $q_k$, whereas communication technology subsidies exclusively hit the high communication cost teams.

A policy of R&D subsidies seems more sensible when immigration policy becomes less feasible. Immigration policy does not require taxation that pulls resources away from other projects. Given that most patents that come from inventors across international borders are organized within firms, the presence of multinational firms would seem to be a useful mechanism for generating this subsidy to communication technology.

I also address the role of education policy in a qualitative manner. Through the lens of the model, education policy follows similar principles to immigration policy. If the cost of training is equal across domains of expertise, then education should be tilted towards classes that have the largest aggregate effects through both their own production channel and the team production channel. Further, fostering diverse expertise will be important for the economy given the rise of diverse expertise in teams.

However, it may be true that the high-value expertises are more costly to train. For instance, organic chemists are extremely valuable because they make contributions across classes. However, it is costly to train organic chemists. This paper has not built a framework to evaluate the mechanisms governing this tradeoff. Because the social value and private value of innovation can be misaligned, this seems like an exciting path for future research.[18]

A key result for education policy is that specific curricula should interact with the team structure of the economy. This is first-order for evaluating how different majors and fields contribute to aggregate innovation. Policy should be tilted towards building expertise that has large aggregate effects, and the policy must recognize the contribution that expertise makes to their productivity alone and to productivity in teams. This paper provides a benchmark for evaluating this issue from a general equilibrium framework.

## C.4 Discussion on Policy Counterfactuals

In order to solve for a counterfactual scenario of an increase of the supply of type $x$ given the existing distribution of skills, I need to solve a high dimensional nonlinear system of equations. However, this process can be simplified by an understanding of the Walrasian equilibrium and methods of tatonnement. The key element is to realize the excess demand function for each type is linked through the team formation equation as follows.

$$m_k = \exp\left(\frac{1}{T_k}\sum_{x\in k}\log\frac{m_{\underline{k}}^x}{m} + V_k\right)$$

$V_k$ represents the net value of the team as estimated in the previous section and is known. It has been identified in the previous equilibrium. $m_k$ and $m_x$ are not observed in the counterfactual world. Given the identification of the model, there is a set of $k$ equations for each team, and the market clearing for each type:

[18] Jones and Williams (1998) discuss this misalignment and find that there is significant underinvestment in R&D.

$$\sum_{k \in K(x)} m_k^x = M_x$$

The overall process gets unwieldy. The following definition characterizes a vector of the mass of types alone:

$$\overrightarrow{m_0} = (m_{10}, ..., m_{\underline{k}})$$

And the excess demand equation for each type:

$$D_x^{\epsilon}(\overrightarrow{m_0}) = \sum m_k^x(\overrightarrow{m_0}) - M_x$$

Each excess demand function can be written out as a function of each type working alone, as each team equation is a function of the types working alone. The key condition is the following condition.

$$\begin{bmatrix} D_1^{\epsilon}(\overrightarrow{m_0}) = 0 \\ \vdots \\ D_x^{\epsilon}(\overrightarrow{m_0}) = 0 \\ \vdots \\ D_X^{\epsilon}(\overrightarrow{m_0}) = 0 \end{bmatrix}$$

The key result for counterfactuals is to find the tattonment equilibrium that satisfies these conditions. This enables the second quantitative exercise that explores changes in the supply of types. Instead of a high dimensional unwieldy equation, there are simply the same number of equations as the number of types.

# D Robustness

First, I ask how the outcome changes with a different measure of patent quality—the private value of patents from the stock market and the *level* of citations. Second, I ask how measuring individual skills only including sole-authored patents (so as to not introduce any possible skill mismeasurement due to team complementarities) affects the outcome measure. Third, I focus on measuring the average distance across types by distance (e.g. average log miles across types) as a measure of the communication cost. Fourth, I extend the time period to see if we can garner more general lessons into the 21st century. Lastly, I focus on potential concerns around endogeneity of the skill measure, and the cases in which it would be concerning, and show that the sources of endogeneity do not lead to concerns.

Overall, the main messages from the previous sections are robust to these different measures, though the quantitative results are slightly different. The changing nature of the benefits of teams is the largest driver behind the rise of teams; taxes have significant effects on production simply through the sorting channel; Russian immigrants produce greater innovation than expected due to self-selection and team formation. Table D.6 summarizes the main differences depending on changes in each measure.

**Measure of Patent Quality.** The patent quality measure (e.g., log average citations) may not measure quality relevant to agents on the patent. I address this concern in two ways. First, I take the stock market value of a patent, applying a measure from Kogan et al. (2017) . This measure is invariant to time period, so one does not need to worry about renormalization. Further, since this captures the private value of patents, it should affect the sorting behavior of teams. Second, I look at the *level* of citations, re-normalized each period. This can be seen in rows $(ii)$ and $(iii)$ in Table D.6 respectively. I find similar results in both cases when it comes to the forces behind the rise of teams, and implications in tax and immigration policy.

**Measure of Expertise.** To measure individual expertise, I take the most prominent class of an individual, adjusting by team size for characterizing skill in class $s$,

$$x_s = \sum_{p \in s} \frac{q_p}{T_p},$$

where $q_p$ is patent impact and $T_p$ is the size of the team on the patent. For the skill in each class by type, I take the average skill vector within each type. Yet, there may be concerns about extracting an incorrect skill through the team collaboration. I turn to sole-authored patents to ensure similar results when I have a correct definition of expertise. The results are qualitatively similar, as we see in Table D.6.

**Endogenous Team Formation.** The framework in this paper incorporates endogenous selection into teams. One concern may be related to the fact that individuals select into teams based on margins that are unidentified in the data (e.g., certain types within types). I address this on two margins. First, I look across the *vertical* dimension of skill, to see whether more skilled people working alone are more or less likely to produce higher quality innovations in teams. I find that, across these measures of expertise, there is no significant difference in the propensity to join teams, and it does not change across time periods. Second, I ask whether individuals working on teams of various vertical skills show heterogeneous returns to teams. Similarly, the effects do not appear to be significant. I address this in Equation (14):

$$y_{p(k,s)} = \alpha_0 + \sum_{j=2}^{3} \alpha_j \mathbb{I}\{Terc(S) = j\} \times \mathbb{I}\{team\} + \sum_{j=2}^{3} \alpha_j \mathbb{I}\{Terc(S) = j\} \times \mathbb{I}\{90s\} + \mathbf{Z}_{p(k,s)} + u_p, \tag{14}$$

$y_{p(k,s)}$ is the outcome of interest, $\mathbb{I}\{team\}$ is an indicator of whether the patent is a team patent or the quality of the patent. When the team indicator is the outcome of interest, I drop it from the right-hand side. Skill $S$ is the total patent impact of the individual, net the focal patent. $\mathbf{Z}_{p(k,s)}$ represents patent-level controls for technology, type, and year. The coefficients from Equation (14) can be found in Table D.5. I focus in particular on the interaction between the skill bins and the marginal effect on patent quality. In particular, the marginal returns to teams appear to be unrelated to the vertical dimension of skill.

Table D.5: Effect of Skill Type on Propensity to Join Team and Patent Quality

| | (1) | (2) |
|---|---|---|
| | Join Team | Log Citations |
| Skill Type 2 | 0.009 | 0.182*** |
| | (0.005) | (0.018) |
| Skill Type 3 | 0.008 | 0.326*** |
| | (0.009) | (0.034) |
| Skill Type 2 × 1990s | 0.005 | 0.040*** |
| | (0.004) | (0.01) |
| Skill Type 3 × 1990s | 0.011 | 0.118** |
| | (0.006) | (0.039) |
| Skill Type 2 × team | . | -0.039** |
| | () | (0.012) |
| Skill Type 3 × team | . | -0.072** |
| | () | (0.025) |
| Observations | 3338119 | 3338119 |
| $R^2$ | 0.051 | 0.121 |
| Technology/Year Controls | Y | Y |

*Notes:* Column (1) treats the team as a $y$ variables in Equation (14). Column (2) looks at citation output and interacts the skill tercile with team. Robust standard errors in parentheses.
*, **,***: Significant at 5%, 1% and 0.1% level respectively.

Table D.5 shows that the propensity to join teams conditional on skill level is not significantly different for different terciles of *vertical* skill, when technology is controlled for. However, the returns to skill of joining teams are marginally lower for the top 2 terciles of skill (about 3–7% lower for the top two terciles of skill). However, since the propensity does not differ, the interaction point of these forces does not appear to be an important ingredient in the changes in team size.

**Quantitative Robustness.** Table D.6 compares the benchmark calibration outcomes to their outcomes when a new measure is introduced. The table takes the $(i)$ benchmark calibration and then performs the same analysis with $(ii)$ the stock market value as a measure of quality; $(iii)$ citation level (instead of log) as measure of quality; $(iv)$; including only sole-authored production to measure skill, and $(v)$ using average distance across types to proxy for geographical communication costs, and $(vi)$ using unique region counts on a patent to proxy for ease of communication costs.

With each of these adjustments, I re-evaluate the main three results of the paper and find they are robust to the alternate definitions. First, I evaluate the joint contribution of benefits, costs, and inventor composition (supply) to the shifting size of teams in the last two decades of the 20th century. Second, I evaluate the innovation impact of taxation and compare the innovation cost of a 10% tax on net output to the benchmark. The fifth column studies the relative impact of Russians compared to their predicted impact, and I find that in all specifications the realized impact is larger than the predicted impact not taking into account self-selection and team production.

There are a few takeaways from Table D.6. First, the changes in idea production seem to be the strongest force in shifts to team production, but in some cases communication costs appear more significant than others, yet never more significant than changing idea production.[19] Second, self-selection in immigration and taxation both have a significant impact on aggregate innovation. This indicates the sorting pattern has important policy implications that can't be ignored from an innovation perspective. Lastly, when I change the definition of geographical distance, it does not affect the tax or immigration policy, since these policies were analyzed with the location information removed.

[19] To point out a caveat when distance is used to measure communication costs. For the decomposition, there is still residual unexplained variation from specific teams that occur more or less frequently than the quantitative model predicts. As a result, the percentages in the three rows do not necessarily add up to 100%. Indeed, some rows on their own might predict a larger than 100% effect.

Table D.6: Robustness — Decomposition and Policy Counterfactuals

| | **Benefits** | **Costs** | **Supply** | **10% tax cost** | **RU impact** |
|---|---|---|---|---|---|
| *(i) Benchmark Calibration* | 68% | 41% | -9% | 7% | 1.56 |
| *(ii) Stock Market Value as Quality* | 102% | 3% | -5% | 7% | 1.27 |
| *(iii) Citation Level as Quality* | 44% | 53% | 3% | 2% | 1.13 |
| *(iv) Sole-Author as Expertise* | 73% | 20% | 7% | 15% | 1.04 |
| *(v) Average geographical distance* | 47% | 36% | -2% | Same | Same |
| *(vi) Unique regions* | 68% | 25% | -9% | Same | Same |

*Notes:* This table reruns the main analysis in the paper varying the definition of skill and output. Source: USPTO, FIPS and author calculations.

## D.1 Expansion into New Team Type

I summarize the share of each team in Table D.7. Here, I show how more expertise is present on new patents (0.48 in the 1980s to 0.58 in the 1990s). Additionally, there are more people with the same expertise. This illustrates how expanding teams expands both the breadth and depth of team expertise.

Table D.7: Expansion of expertise

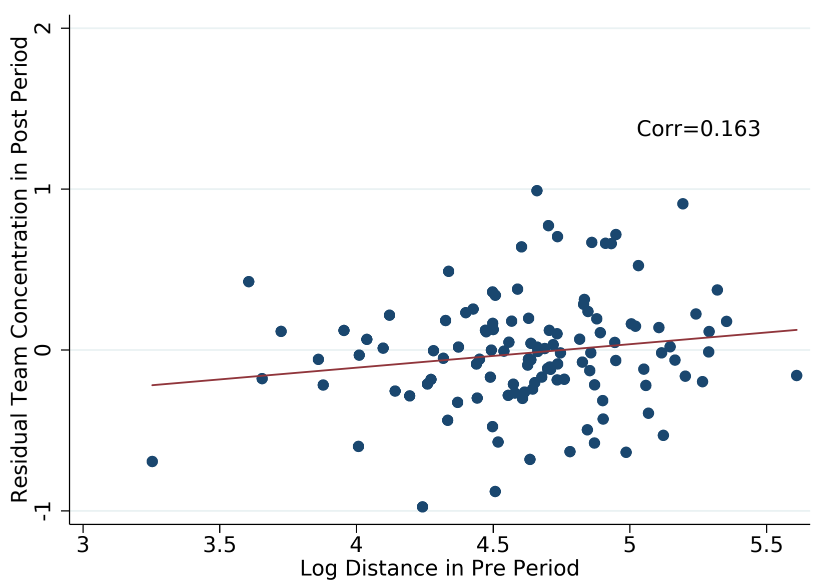
| **Outcome** | **1980s** | **1990s** |
|---|---|---|
| Share of patents w/ more than one expertise | 0.48 | 0.58 |
| Share of patents of 2 or more w/ same expertise | 0.17 | 0.25 |

*Notes:* Counts expertise as experience in patent technology class. Source: USPTO and author calculations.

## D.2 Communication Costs and Regional Dispersion

I estimated 41% as the upper bound for the marginal effect of communication costs on the change in team size. To ensure that the residual from patent quality is picking up changes in communication costs, I evaluate the correlation of the rise of team types not determined by changes in quality with the initial communication costs between those team types. For the focal measure of communication costs, I evaluate the spatial distance between types. I plot the residual increase in team type against the log of the mean distance in miles across the types. The intuition is the following: if the frequency of a spatially distant match is increasing without a corresponding increase in the patent quality of the match, it is likely this increased match is explained by some reductions in communication costs. Figure D.8 shows this relationship.

Figure D.8: Change in Team Count and Avg. Unique Locations in Pre-period




While the correlation is significant, there is still residual variation unexplained by the distance, which results from certain teams forming without a corresponding increase in output. I leave the specific discussions of team types that rise without changes in the return to teams or spatial communication costs to further research.