Borrowing for Breakthroughs: Student Loans and Innovation*

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Abstract

We investigate how higher education financing shapes innovation. Linking administrative patent records to consumer credit data, we document new facts about household finance and invention and apply the design of Black et al. (2023) to patenting. The design uses expansions in federal Stafford loan limits as a source of variation in first-year borrowing to estimate effects on subsequent patenting. We estimate large, albeit imprecise, effects of loan availability on future innovation, among the previously constrained population of students who responded to these policy changes. Point estimates of percentage responses are similar or larger for highly cited patents, consistent with a "lost Einsteins" hypothesis in which financing barriers impede high-potential innovators. The findings suggest that easing constraints on educational investment can generate innovation benefits beyond students' private returns, making education financing a potential lever for innovation policy.

JEL: I22, G51, J24, H52, O31

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"When it comes to technological innovation, we are rowing with one hand tied behind our back."
—Michelle K. Lee, former U.S. Under Secretary of Commerce for Intellectual Property, testimony before the House Judiciary Committee hearing "Lost Einsteins: Lack of Diversity in Patent Inventorship," March 2019

1 Introduction

Although economists have long viewed innovation as a key driver of economic growth, systemic barriers stifle the innovative potential of many talented Americans. The amount of innovation that leaks out of the pipeline is alarming: equalizing innovation rates across gender, race, and parent background could result in as much as four times as many inventors in the next generation (Bell et al., 2019b), which could increase long-run economic growth by 14% (Brouillette, 2025). Identifying which programs and policies can reduce these gaps remains an important empirical question.

This paper investigates whether higher education financing can be an effective policy lever to bring talented students into the innovative ecosystem. Specifically, we apply an established research design for studying student loan availability to a new downstream outcome: patenting. Our linked dataset also allows us to document novel stylized facts about the household finance side of innovation.

Existing evidence and economic theory offer ambiguous predictions about how the generosity of student loan policy shapes innovation. On the one hand, student loan availability can increase access to higher education and allow students to focus more on education instead of working while in school (Black et al., 2023; Card and Solis, 2022). The positive "human capital" effect of student loans may increase students' future innovation. On the other hand, because innovation is often viewed as a risky career with potential payoffs accruing later in life (Bell et al., 2019b; Akcigit et al., 2017), the "debt overhang" channel may push students to pursue higher-paying and less risky careers (Field, 2009; Rothstein and Rouse, 2011; Krishnan and Wang, 2018).[1] Debt can also shape educational and occupational choices before

[1]Prior literature has emphasized the effects of debt overhang in pushing students away from careers with social spillovers. For instance, Rosenblatt and Andrilla (2005) find that medical students are less likely to enter into primary care (with high public demand but low wages) if they hold student loans than medical students without student loans, though the effects are modest when demographic characteristics are taken

graduation, so the two channels may interact at the stage of field choice as well as subsequent career choice. Related work examines how student borrowing shapes careers and subsequent financial outcomes (Minicozzi, 2005; de Gayardon et al., 2018; Gervais and Ziebarth, 2019; Daniels Jr. and Smythe, 2019; Black et al., 2023; Sauers, 2023).

To produce new empirical evidence on how student loan policies shape innovation, we link USPTO administrative patent records to individual-level consumer credit records, including detailed student loan origination and repayment information, in a quarterly panel spanning 2004 to 2021. The resulting dataset tracks nearly 250,000 US inventors—roughly a third of all inventors in the country—and their observed credit histories. To our knowledge, no prior study has linked administrative patent records to individual-level credit bureau and student loan data at this scale. This linkage brings together credit-market experiences early in life and subsequent invention, enabling us to study policy variation in education financing as well as descriptive relationships. It extends the evidence on higher-education financing beyond private labor market outcomes to innovation, an outcome with potentially important social spillovers.

We find a positive relationship between policy-induced access to student loans and subsequent patenting. Following the difference-in-differences instrumental variables design of Black et al. (2023), we compare borrowers classified as constrained by the pre-reform Stafford limit with other borrowers across cohorts exposed to expansions in loan availability. Absent the expansions, we assume the average patenting difference between borrowers classified as constrained and the remaining borrowers would have been the same across exposed and unexposed cohorts. Subject to that assumption and the IV interpretation discussed below, the estimates imply 0.45 additional patent filers per 1,000 borrowers for a $1,000 increase in first-year borrowing, equivalent to 74% of the sample mean. At the pre-reform borrowing limit and the sample patenting rate, this corresponds to an implied elasticity of approximately 1.9. The estimate is imprecise: an approximate 95% confidence interval extends from 0.67 to 3.22. We therefore view the large point estimate alongside the more modest responses

into account. This comports with the findings of Rothstein and Rouse (2011) relating to public-interest careers. Other studies have suggested that the psychology of debt matters a great deal in pushing students away from public interest careers: In an experiment at NYU's Law School studied by Field (2009), two career-contingent financial aid packages with equivalent monetary value were randomly assigned to students, and the negative psychological effects of student loans pervade into more than just initial job choice.

with which it is statistically consistent.

The historical borrowing margin provides important context for this magnitude. These borrowers were pursuing education despite financing constraints and were willing to take on additional debt when the limits increased. Such choices may reflect substantial expected benefits from education, including access to careers requiring advanced training. Additional financing can therefore enable particularly valuable investments among students already committed to pursuing them. This selection helps explain why patenting could be highly responsive at the margin studied here; Section 6.1 develops the interpretation and relates it to other student-loan policies.

Point estimates expressed as percentage changes are similar or larger for highly cited patents when compared with patenting overall. This pattern is consistent with the "lost Einsteins" hypothesis of Bell et al. (2019b): financing barriers may prevent high-potential innovators from developing their talents.

Although little is known about direct impacts of student loans on innovation, the literature has established some evidence that student loans negatively impact entrepreneurship (Lammers, 2015; Checovich and Allison, 2017; Krishnan and Wang, 2018; Desai et al., 2020). While different from innovation, there is overlap in the skillsets and risk profiles, and starting a firm is often in practice a means of commercializing one's innovation. This evidence highlights a reason debt burdens could discourage invention. Expanded loan availability, however, can improve educational opportunities at the same time that it increases debt; our estimates concern the net response to that financing change rather than the debt-burden channel in isolation.

Our findings motivate considering education financing as part of the innovation-policy portfolio. If financing barriers prevent students with high inventive potential from undertaking valuable educational investments, relaxing those barriers can have benefits beyond the students' own earnings. The policy question is therefore not only how much financing to provide, but which students have valuable educational opportunities that a binding constraint prevents them from pursuing fully.

The remainder of the paper is organized as follows. Section 2 provides background on U.S. student loan programs and the policy changes we exploit. Section 3 describes our novel

linked dataset connecting patent and credit bureau records. In Section 4, we document new descriptive facts on the relationship between household finance and innovation. Section 5 outlines our empirical strategy and identifying assumptions, and Section 6 presents the estimates and their interpretation. Section 7 concludes with a discussion of policy implications and directions for future research.

2 Student Loans in the US

Over the last two decades, student loans have become an increasingly prominent form of debt for many individuals in the U.S. As shown in Figure A1, aggregate student loan debt balances in the U.S. rose from $240 billion in 2003 to $1.6 trillion in 2024 (nominal dollars). During this period, student loans became the third largest category of debt behind mortgages ($12.6 trillion) and auto loans ($1.6 trillion).[2] In terms of aid to access education, student loans are a significant form of aid to undergraduates. Almost 40% of full-time undergraduate students were awarded some form of federal student loan in 2020 (National Center for Education Statistics, 2023). The federal government primarily makes student loans available to borrowers.[3]

For decades, the bulk of federal student loan programs were provided under the Stafford Loan program. Stafford Loans are loans made available by the United States federal government to students attending accredited higher-education institutions. For undergraduates, borrowers may access loans up to a specific dollar amount based on their dependent status and their years of enrollment. Undergraduate students may be eligible for either subsidized or unsubsidized loans based on financial eligibility determined by the Free Application for Financial Student Aid (FAFSA). Subsidized loans do not accrue interest while students maintain an enrollment status of at least half-time. In addition, from 2008 to 2013, subsidized loans had a slightly lower interest rate.

The Stafford Loans borrowing limit experienced two significant increases in the last two

[2]See Center for Microeconomic Data (2024) for additional details.

[3]Ma et al. (2024) estimates federal student loan lending comprises between 75% and 93% of all education borrowing each year with non-federal student loan amounts coming from states, post-secondary institutions and private markets.

decades. The Higher Education Reconciliation Act of 2005 raised borrowing limits from $2,625 to $3,500 and $3,500 to $4,500 for first-year and second-year students, respectively. These new limits went into effect for the 2007-2008 academic year, which began on July 1, 2007. The Ensuring Continued Access to Student Loans Act of 2008 increased borrowing limits for the 2008-2009 academic year. First-year borrowing limits increased from $3,500 to $5,500, second-year limits increased from $4,500 to $6,500, and finally third-, fourth- and fifth-year students' limits increased from $5,500 to $7,500. Table 1 summarizes these changes for each academic cohort by enrollment year. The Stafford Loan program stopped offering loans for the 2010-11 academic year and was replaced by the Federal Direct Loan Program, which preserved the limits established by the Ensuring Continued Access to Student Loans Act of 2008.

Table 1: Loan limits by entry cohort and academic level

	Academic level (year in school)					
Entry cohort	1st	2nd	3rd	4th/5th	Total	Relative
2004-05 and earlier	$2,625	$3,500	$5,500	$5,500	$17,125	-
2005-06	$2,625	$3,500	$5,500	$7,500	$19,125	$2,000
2006-07	$2,625	$4,500	$7,500	$7,500	$22,125	$5,000
2007-08	$3,500	$6,500	$7,500	$7,500	$25,000	$7,875
2008-09 and later	$5,500	$6,500	$7,500	$7,500	$27,000	$9,875

Notes: This table shows the Stafford Loan borrowing limits for dependent undergraduate student loan borrowers by entry cohort and academic level. Column (6) shows the aggregate loan amount available to borrow for each entry cohort over the course of their four years of enrollment. Column (7) shows the cumulative amount in Column (6) relative to the 2004-05 entry cohort. The entry cohort "2004-05 and earlier" applies to cohorts from 2001-02 to 2004-05. Stafford Loan limits were different for cohorts before the 1995-96 academic year, but our sample begins with cohorts in 2001-02. Source: Federal Student Aid (2006, 2007, 2008)

3 Data

Our main source of data on student loans comes from the University of California Consumer Credit Panel (UC-CCP). The UC-CCP consists of quarterly loan-level credit records from an anonymized longitudinal panel of over 70 million individuals. As described in Section 2, borrowing limits vary by an individual's enrollment year and academic level. However, while the UC-CCP contains detailed information on individual loans, it does not directly identify

borrowers' enrollment or dependent-undergraduate status. In order to identify the first-year of enrollment of borrowers, we assume the first year of enrollment coincides with the first year of borrowing. More specifically, we define a borrower's academic year of enrollment if they first took out a loan during that academic year. For example, if a borrower's first education loan originated on September 24, 2004, then their enrollment year is defined as 2004-05 since that origination date falls within July 1st, 2004 and June 30th, 2005. One limitation of the UC-CCP is that the panel only begins in 2004. For loans that remain visible in the panel, reported origination dates and amounts allow us to reconstruct borrowing before 2004, covering our earliest entry cohorts.

The credit dataset consists of loan-level credit records from a consumer credit bureau totaling 60 million individuals each quarter from 2004 to 2021. The data include a complete sample of every individual with a credit record in California and a 2 percent random sample of individuals with a credit record in the U.S. For a complete picture of household borrowing, the dataset also includes the credit records of all household members and associated borrowers (e.g., co-signers or joint-account holders) of each individual sampled. Even after an individual leaves California, the credit panel continues to observe the credit records of the individual along with their household members and associated borrowers. In other words, an inventor does not necessarily need to live in California at time of invention to be in the 100 percent California sample if the inventor lived or studied in California in an earlier year. For instance, a student who studied in California in 2004 but has lived in Texas since would remain in the UC-CCP for each year since moving out of CA. While our paper has a national scope, we see the 100 percent coverage of California as a strength on top of the 2 percent national sample. In particular, California is the most useful state to over-sample because although it only accounts for 12 percent of the U.S. population, we find that it accounts for nearly one quarter of all U.S. patents, which is far higher than any other state.

A patent is an exclusive right granted by the government to an inventor for a product or process. Most but not all patents are assigned to firms by their inventors, and the term is generally 20 years from the filing date. The United States Patent and Trademark Office (USPTO) is the entity responsible for evaluating and approving patent applications in the U.S. In 2020, the USPTO received 646,244 applications and issued 388,900 patents.

An example of one such granted patent is shown in Figure A2, which helps convey the richness of the data available. Data on inventors and their patents are sourced directly from the USPTO. This dataset is built from administrative records first made public in response to the Obama administration's Open Government Initiative; we use the Patent Examination Research Dataset (PatEx) dataset produced by Graham et al. (2018), which contains two types of documents. First, it contains all patents granted since approximately 1980. Second, it contains most patent applications that were filed—regardless of whether they were granted—since the passage of the American Inventors Protection Act (AIPA) heavily incentivized application publication beginning in late 2000. We define an individual as an inventor if they are listed as an inventor on a patent grant or application during the timeframe for which we observe individuals in the UC-CCP, which runs from 2004 to present. Following Bell et al. (2019b), we include all individuals listed as inventors, not just those assigned intellectual property rights. In particular, inventors employed by firms are listed as inventors while their firms are listed as assignees.

Our main approach to measuring patent value is the number of citations a patent has received from future patents. Because more recent patents have mechanically had less time with which to accumulate citations, we define a citation-based ranking relative to other patents granted in the same year. Though still not a perfect measure of quality, Bell et al. (2019b) have established that inventors of higher-cited patents earn more than inventors of patents with fewer citations, suggesting that citations may be a reasonable proxy of quality. Griliches (1990) points out that there is good empirical support to view patents as a proxy for innovation because a very robust relationship exists across firms between expenditures on R&D and patent output. Still, many important innovations are not patented (or patentable), and many patents do not correspond to real innovation. We examine citation-based thresholds in Section 6.2 to assess whether the estimated response also appears among more highly cited patents. Prior work by Hall et al. (2005) linking patent records to Compustat has established that firms with more highly cited patents have higher stock market valuations. These measures provide information about patent quality, but do not measure the full social value of invention.

For every student loan borrower in the credit data, we observe detailed information

on each of their loans. Variables include the loan origination date, original loan amount, remaining balance, and scheduled payment amount for every quarter that the loan provider reported information to the credit bureau. In addition, even loans that have been closed will remain in the credit bureau data for up to seven years. We also have limited information on the characteristics of the borrowers. For each borrower, the dataset includes birth year and month, household composition, ZIP Code, and Census Block.

There are two key limitations to the credit panel data. First, the data do not contain high-quality self-reports of individuals' race and ethnicity. We therefore rely on imputed demographic variables available from the credit bureau, along with individual-level race and gender imputations derived from names in the patent records. Second, not all people have credit records: an analysis by Brevoort et al. (2016) suggests as many as 26 million adult Americans may be lacking credit reports, and this population of so-called "credit invisibles" is concentrated among the young or elderly, racial minorities, and low-income consumers. We expect the incidence of credit invisibles among both student loan holders and inventors to be low. Thus, the issue of absence of credit reports is unlikely to significantly impact our record linkage rate and analysis. Despite these caveats, we believe the lack of alternative data sources and the importance of the research question justify this approach, and we note throughout where our methodologies are designed to mitigate the impact of these limitations.

4 Descriptive Results

Given the novelty of our linked dataset, we highlight several stylized facts about credit histories and student loan usage among inventors.

Table 2 summarizes the data. Applying imputation methods for race and gender, we find that 88% of our linked inventor sample is White or Asian (relative to 60% of the general CA population) and 17.5% are women. These roughly align with already existing estimates of the demographic backgrounds of inventors (Bell et al., 2019b).

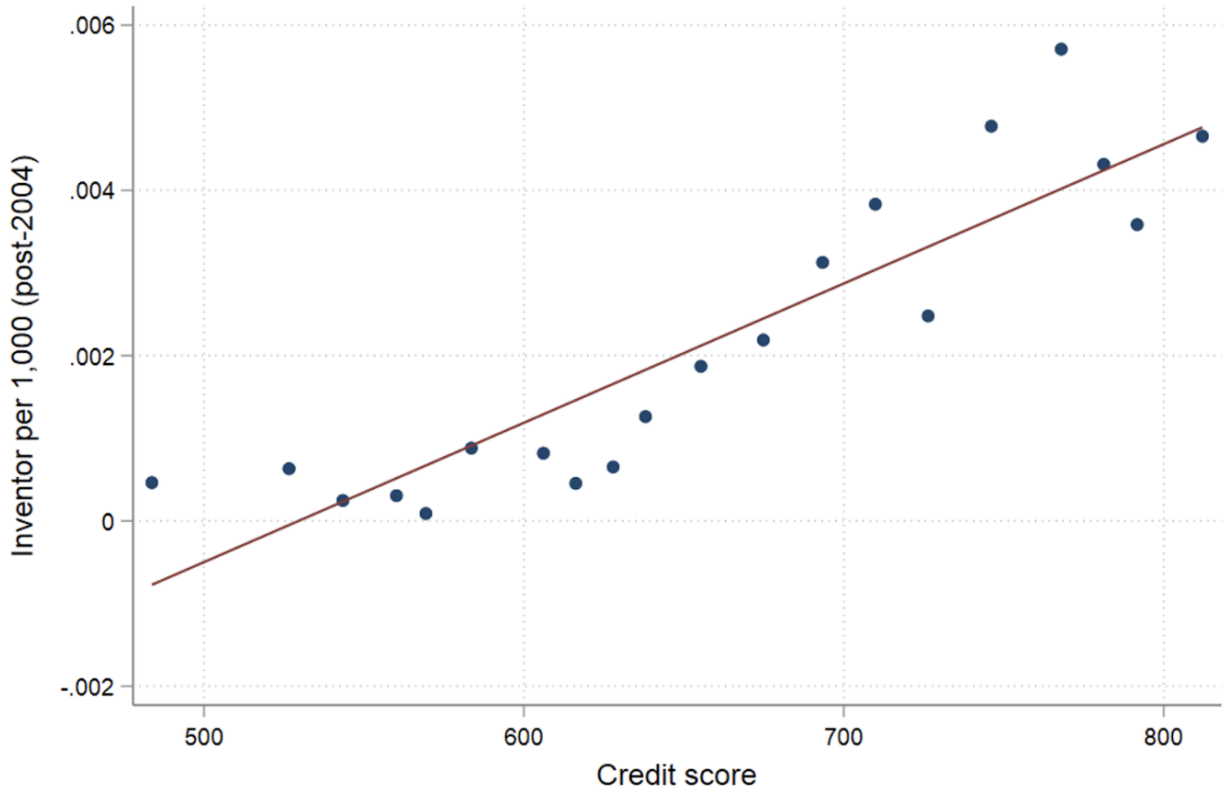
Table 2: Descriptive Statistics

	Inventor	Non-inventor
BISG Race Probability		
White	0.611348	0.448608
Black	0.030516	0.069227
Latino	0.074786	0.320737
Asian Pacific Islander	0.257257	0.13684
Female	0.175	0.466
Credit score	761	677
Share with student loans	0.066	0.111
Amount of student loans ($)	2,544	3,707

Notes: Variables measured in most recent year available.

Figure 1 shows how the likelihood of filing a patent varies with credit scores at the start of the sample. We find that inventors' credit histories are quite good: People with credit scores in the top 10% of the distribution are ten times as likely to invent as those with below-median credit scores.

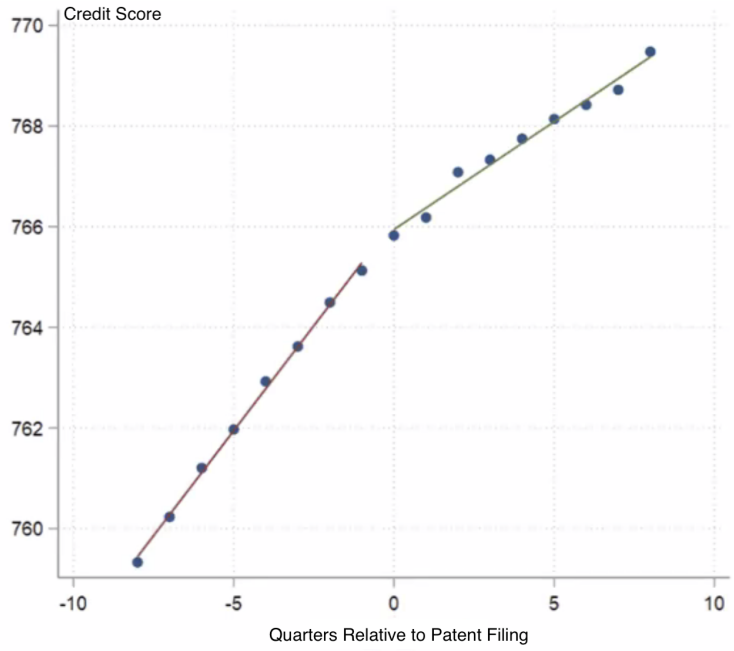
Figure 1: Innovation Rates by Credit Score



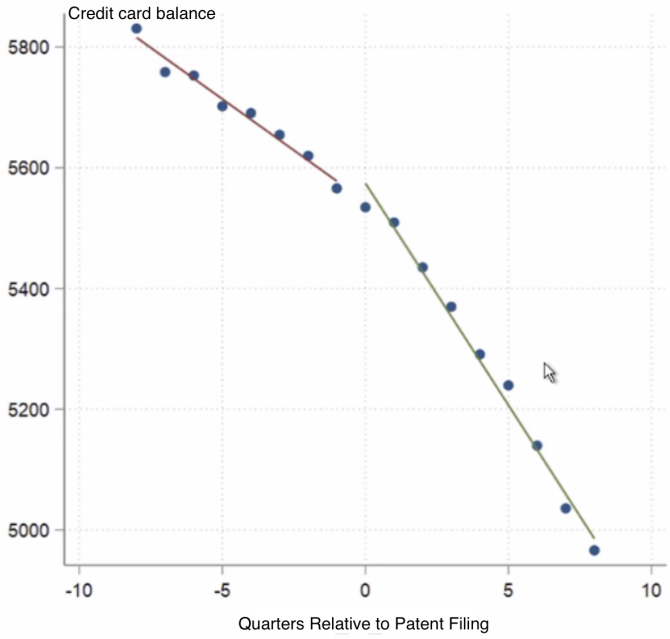
Notes: This figure plots innovation rates (per 1,000) by credit score in 2004.

We do not observe a sharp improvement in these credit-market measures around the average patent filing. Panel A of the event studies in Figure 2 shows that credit scores are increasing, but if anything increase somewhat more slowly after the time of innovation. Panel B shows a similar analysis for credit card usage, a rough indicator of household financial activity rather than a direct measure of consumption. If anything, credit card usage also exhibits a decline relative to trend following an innovation. These descriptive patterns complement work on the private returns to innovation (Depalo and Di Addario, 2014; Bell et al., 2019a; Kline et al., 2019); they do not by themselves identify those returns.

Figure 2: Event Studies Around Patenting



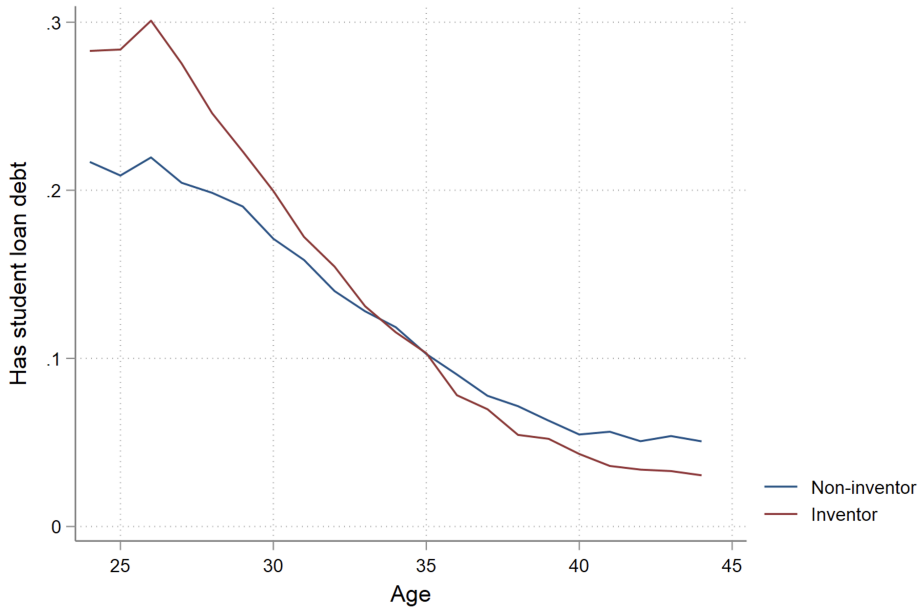
(a) Credit score



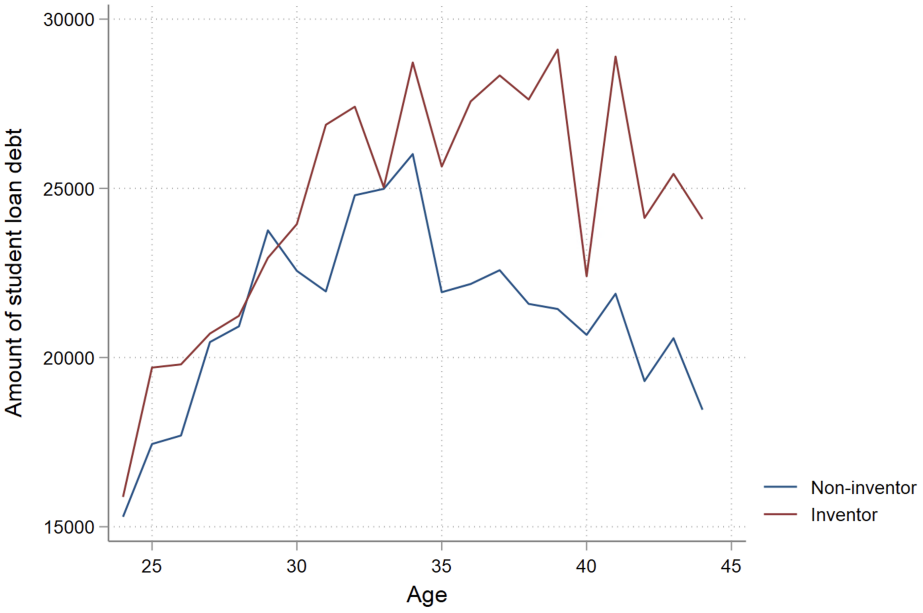
(b) Credit Card Balance Amount

Notes: Panel (a) shows credit scores around the time of innovation. Panel (b) shows a similar analysis for credit card usage. For individuals with more than one patent in the sample frame, we choose a random one as the event.

Figure 3: Student Debt Over the Lifecycle



(a) Share of Observations with Any Student Loans



(b) Amount of Student Loan Debt

Notes: Panel (a) plots the share of individuals in the credit panel that have student loans by age, separately by whether the individual has filed a patent or not. Panel (b) plots the amount of loans, among those that have any loans. Age and student loans are both measured in 2004, and inventor status is aggregated over all years since 2004.

Figure 3 investigates how student loan amounts accrue to inventors over the lifecycle.

During their early 20s, inventors accumulate substantially more student loan debt than most people, but also pay off the debt more quickly; by age 40, inventors are actually substantially less likely to hold any student loan debt than their peers.

5 Empirical Framework

Following Black et al. (2023), we use first-year borrowing to identify borrowers likely constrained by the pre-reform Stafford limit. Borrowers at the old limit before the expansion, or between the old and new limits afterward, are classified as constrained. We compare subsequent patenting among borrowers classified as constrained with patenting among the remaining borrowers in our estimation sample, across cohorts with different exposure to the expansions.[4]

The identifying assumption is that, had loan limits remained unchanged, the average patenting difference between borrowers classified as constrained and the remaining borrowers would have been the same in cohorts exposed and unexposed to the expansions. Borrowers classified as constrained may have a different underlying propensity to patent; identification requires that this difference would not have changed across exposed and unexposed cohorts absent the reforms. Black et al. (2023, Sections II.C and III) discuss the identification argument in detail.

We first use an event-study specification to display the borrowing and patenting differences between borrowers classified as constrained and the remaining borrowers in each cohort, relative to the 2004-05 cohort. The pre-policy coefficients describe how these differences evolved before expanded loan availability; the post-policy coefficients trace the response to the expansions.

$$y_{ic} = \beta_0 + \beta_1 Constrained_i + \sum_{j \neq 2005} \beta_c Constrained_i \times \mathbf{1}\{j = c\} + \delta_c + \varepsilon_{ic} \tag{1}$$

where y_{ic} refers to the dependent variable of interest for individual i in cohort c. Our sample consists of cohorts from academic year 2001-02 ($c = 2002$) through 2012-13 ($c = 2013$).

[4]This design has subsequently been applied in other work, including by Sauers (2023).

The coefficients of interest for the event graph specification in Equation 1 are on the interaction terms, $\beta_c Constrained_i \times \mathbf{1}\{j = c\}$. Finally, we include cohort fixed effects denoted δ_c.

Our main regression specification takes the following form:

$$y_{ic} = \alpha + \beta_1 Constrained_i + \beta_2 Constrained_i \times \mathbf{1}\{c > 2005\} + \delta_c + \varepsilon_{ic} \tag{2}$$

where δ_c corresponds to cohort fixed effects for $c \in [2002, 2013]$. The pooled specification uses an indicator for cohorts after 2004-05. Exposure to the reforms varies within this pooled group: some cohorts could receive higher limits in later years of study before first-year limits changed. We classify borrowers using first-year loan amounts at the old limit or, after first-year limits rise, between the old and new limits.[5] See Table 1 for additional details on Stafford borrowing limits.

To express the patenting response relative to the associated change in borrowing, we follow the instrumental variables approach of Black et al. (2023). We instrument first-year borrowing with the interaction between constrained status and the indicator for affected cohorts. More specifically, we estimate the following system using two-stage least squares:

$$\begin{aligned} y_{ic} &= \beta_0 + \beta_1 Constrained_i + \beta_2 Loans_{ic} + \delta_c + \varepsilon_{ic} \\ Loans_{ic} &= \gamma_0 + \gamma_1 Constrained_i + \gamma_2 Constrained_i \times \mathbf{1}\{c > 2005\} + \delta_c + \eta_{ic} \end{aligned} \tag{3}$$

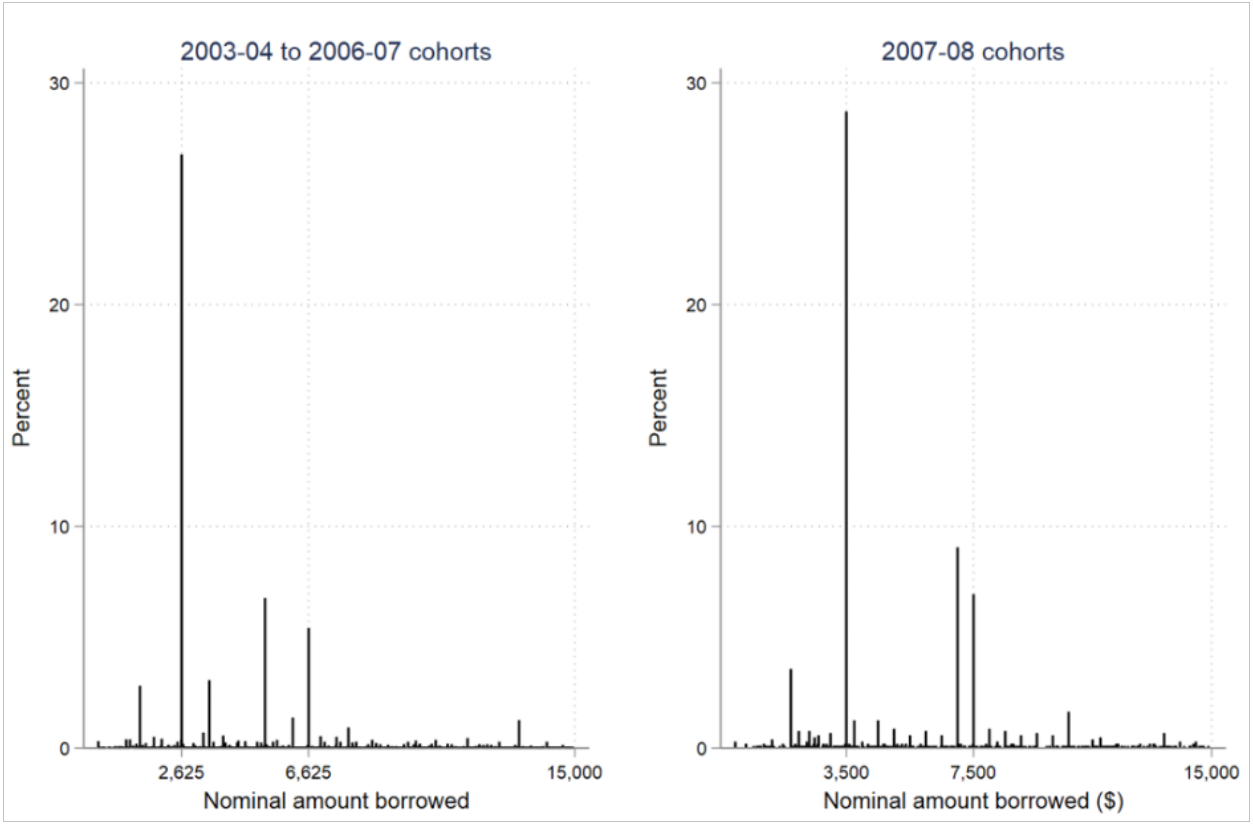
Here $Loans_{ic}$ is first-year borrowing, measured in thousands of dollars. The IV coefficient expresses the patenting response per \$1,000 of policy-induced first-year borrowing. Since the reforms also expanded later-year loan availability, first-year borrowing normalizes the broader financing change. We follow Black et al. (2023, Section IV.D) in distinguishing this scaling from a causal per-dollar interpretation, which additionally requires that the policy affects outcomes through borrowing.

[5] The variable $Constrained_i$ is an indicator that equals 1 for borrowers in cohorts through academic year 2006-07 ($c \leq 2007$) who borrowed exactly $\$2,625$; for borrowers in the 2007-08 cohort ($c = 2008$) who borrowed between $\$2,625$ and $\$3,500$; and for borrowers in cohorts from academic year 2008-09 onward ($c \geq 2009$) who borrowed between $\$2,625$ and $\$5,500$.

6 Estimates and Interpretation

As described in Section 2, the statutory borrowing limit rose for students in the academic cohorts of 2007-08 (denoted as 2008). Figure 4 shows the distribution of loans for earlier cohorts versus the 2007-08 cohort. For both sets of cohorts, we observe bunching at the dependent individual Stafford loan limit, which we exploit for this paper. For the earlier cohorts, the bunching point occurred at $2,625, whereas the mass shifted to $3,500 after the loan limit was raised.

Figure 4: Bunching Response to Policy Change

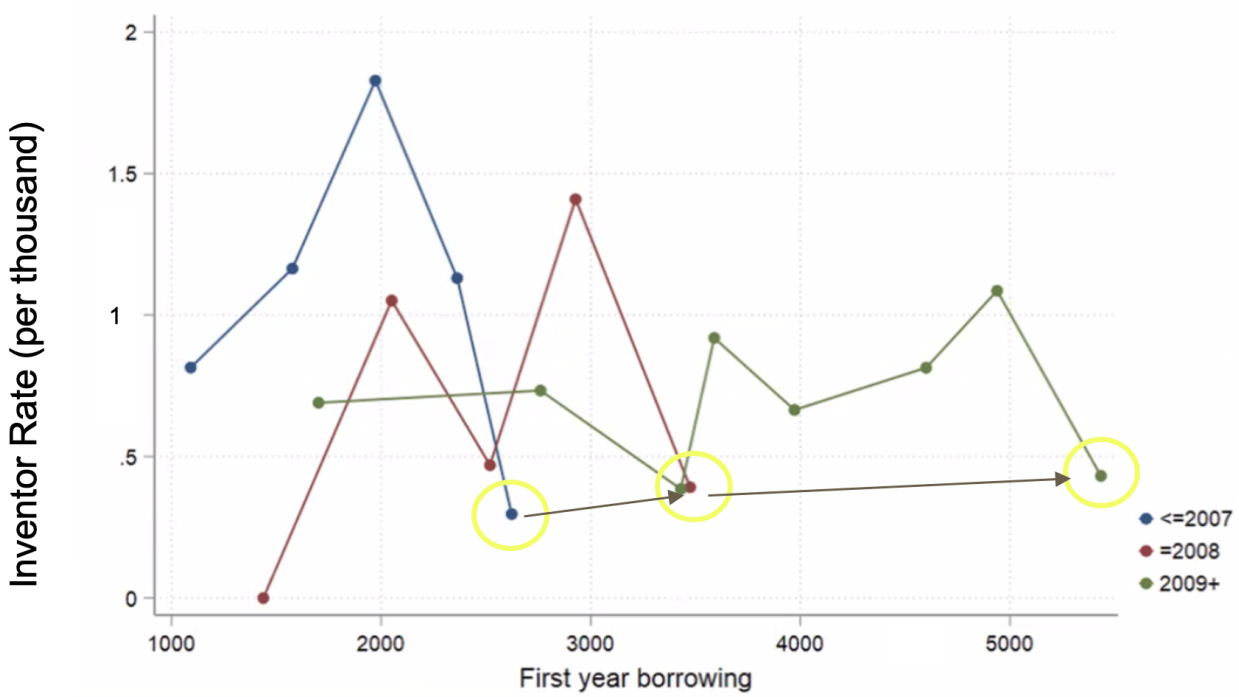


Notes: This figure shows student loan borrowing during first year of college (i.e., the year in which person is observed to have student loans). Source: Authors' calculations based on the UC-CCP. For the earlier cohorts, the individual dependent Stafford loan limit was $2,625 and the non-dependent limit was $6,625. For the 2007-08 cohort, the dependent limit was changed to $3,500 and the non-dependent limit was changed to $7,500.

To provide graphical intuition for the comparison, Figure 5 plots innovation rates by student loan amounts, separately by cohort. Innovation rates are higher among borrowers in the expanded constrained range in subsequent cohorts. This descriptive comparison does not

adjust for overall cohort effects or changing borrower composition; it motivates the regression analysis rather than establishing the policy effect on its own.

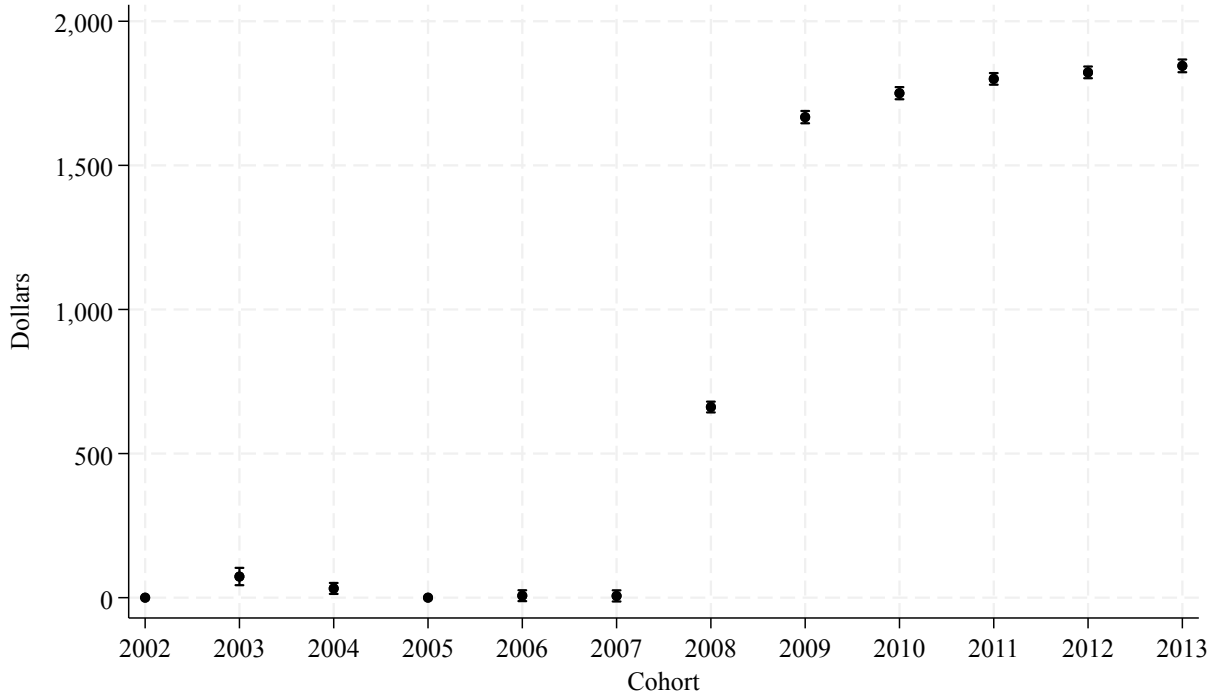
Figure 5: Innovation Rates by First Year Borrowing, by Policy Regime



Notes: This figure shows innovation rates per thousand individuals based on the amount the individual borrowed in their first year of college. For cohorts prior to 2007, the borrowing limit was $2,625, which was raised for the 2008 cohort to $3,500 and for subsequent cohorts to $5,500.

Figure 6 shows how much constrained borrowers actually borrowed additionally relative to unconstrained borrowers in their respective cohorts. Prior to the policy change, the difference within cohorts in borrowing between constrained and unconstrained borrowers remained fairly similar to the academic cohorts of 2004-05 (denoted as 2005). There is no confidence interval for 2005 because that cohort is normalized as the base year. The estimated effect increases by roughly $680 for the 2007-08 cohort, who experienced an increase of $875 in their borrowing limit, and increases by more than $1,700 over the later cohorts, who experienced an increase of $2,875 in their borrowing limit relative to the 2004-05 cohort. The increase in actual amounts borrowed is less than the increase in the limit because not all students borrow at the new limit.

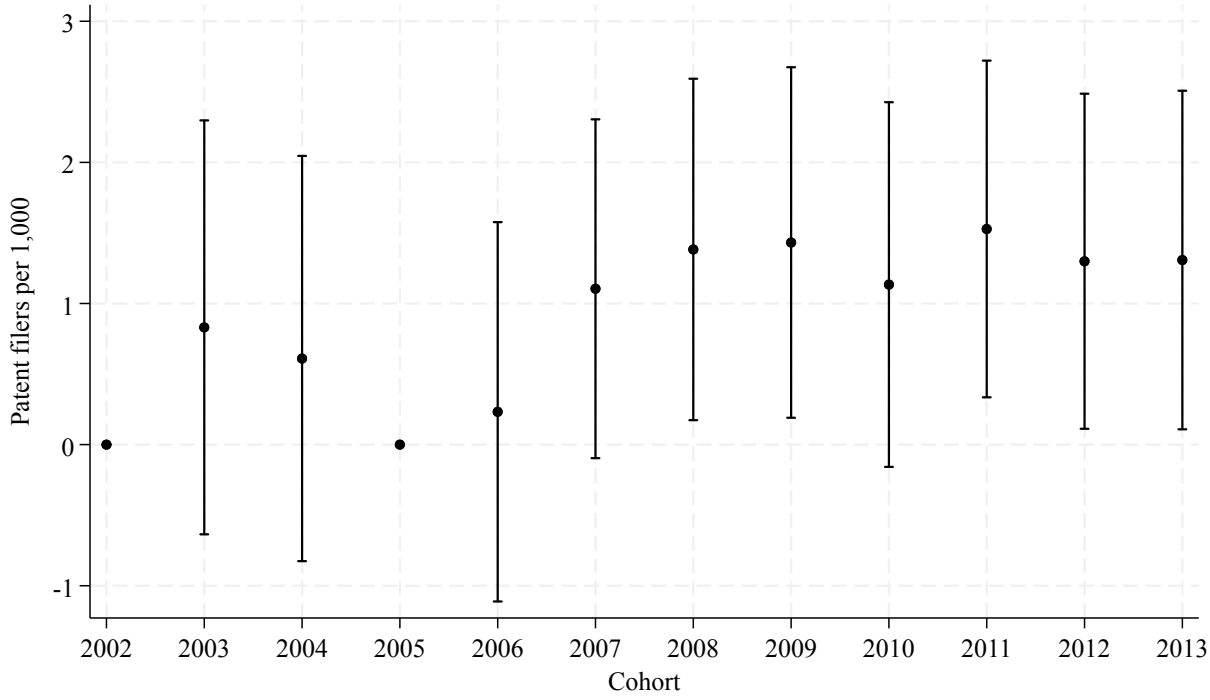
Figure 6: First-Stage Effect of Loan Limits on Borrowing



Notes: Estimated coefficients from the event-study regression specification described in Equation 1 where the dependent variable is first-year borrowing.

Figure 7 shows an increase in patenting among constrained borrowers relative to other borrowers in their cohorts after first-year loan limits rose. The earlier cohort coefficients display the evolution of the patenting gap relative to the 2004-05 cohort. The estimated increase is roughly 1 patent filer per 1,000 individuals in the 2007-08 cohort and onward. This pattern is consistent with a positive effect of expanded financing, subject to the cohort-comparability conditions discussed in Section 5.

Figure 7: Reduced-Form Effect of Loan Limits on Innovation



Notes: Estimated coefficients from the event-study regression specification described in Equation 1 where the dependent variable is patent filers per 1,000 individuals.

Table 3 presents OLS and IV estimates that are helpful for interpreting magnitudes. Columns 1-3 present the naïve OLS specifications, with a varying set of controls. In column 1, without any instrumental variation, we find no significant relationship between amount of loans and future patenting rates. While not significant, here student loan debt is associated with slightly lower future patent rates: $1,000 of first-year borrowing is associated with .044 fewer inventors per thousand (7.2% of the mean innovation rate). Column 2 adds a control for whether the student was constrained (coefficient not displayed), and Column 3 additionally adds cohort fixed effects. While it is clear that innovation rates are lower among constrained students than unconstrained students, there remains no significant relationship between first-year borrowing and future innovation rates.

Table 3: Regression Specifications

Outcome: inventors per 1,000 Mean of outcome: 0.613				
	OLS (1)	OLS (2)	OLS (3)	IV (4)
First Year Borrowing ($1,000s)	-0.0440 (0.0341)	0.0339 (0.0398)	0.0267 (0.0515)	0.454** (0.152)
Cohort Fixed effects	No	No	Yes	Yes

Notes: Regression specification from Equation 3. The outcome is patent filers per 1,000 individuals. Columns 2, 3, and 4 include controls for whether the student is constrained.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Our IV results are presented in Column 4 of Table 3. First-year borrowing is instrumented by the interaction of constrained status and cohort exposure to the loan-limit changes. The coefficient is 0.454 patent filers per 1,000 borrowers for a $1,000 increase in first-year borrowing, with a standard error of 0.152. This is equivalent to 74% of the sample mean. Normalizing by the pre-reform first-year limit of $2,625 gives an implied borrowing elasticity of approximately 1.9, with an approximate 95% confidence interval of 0.67–3.22.[6] Though the point estimate is large, our estimate also carries considerable imprecision.

Notably, our large patenting estimate is also in line with the educational response implied by Black et al. (2023). Their STEM bachelor's completion estimates imply an elasticity of about 1.4 when normalized by cumulative borrowing, or about 1.9 when normalized by first-year borrowing.[7] The similarity is not surprising: enabling more students to complete STEM degrees likely expands the pool of potential inventors. Still, the extent to which STEM degrees translate to patents depends on other factors, including career choice, that may also be impacted by debt directly.

[6]The implied elasticity is $0.454 \times 2.625 / 0.613 = 1.94$. We use the pre-reform cap as the borrowing reference for constrained students, and the broader sample mean of 0.613 patent filers per 1,000 as a proxy for their baseline patenting rate. The interval scales the reported coefficient and standard error while holding these reference values fixed. Detailed calculations and literature benchmarks are available from the authors on request.

[7]Authors' calculations from their Tables 5 and 6 for Texas four-year entrants, using cumulative borrowing through year six or first-year borrowing.

6.1 Understanding the Magnitude

Although it may be tempting to interpret the large point estimate as evidence that student loan reforms today are likely to have large impacts on innovation, economic several nuances to its interpretation (beyond imprecision) suggest caution in extrapolation. We emphasize that the estimate should be interpreted as a LATE, and is most internally valid for a population of students who attended college in a financially constrained system in the early 2000s. There are many reasons to suspect this is a particularly responsive group.

The borrowers whose behavior identifies it were pursuing education despite financing constraints and were willing to assume additional debt to do so. Their willingness to make this investment may reflect substantial expected gains, whether higher earnings or access to a career they value. Students' educational choices depend partly on the gains they expect (Carneiro et al., 2011; Wiswall and Zafar, 2015). When limited resources prevent students from undertaking their desired training, high-return investments can remain unrealized (Lochner and Monge-Naranjo, 2011). Additional financing may then enable more intensive study, continued enrollment, or research experience among students already striving to pursue those opportunities.

If education were allocated entirely according to potential returns, the highest-return students would already receive the most training. When family resources and other barriers also govern access, some high-potential students instead remain undertrained. Missed selective-college opportunities among high-achieving, low-income students (Hoxby and Avery, 2013) and socioeconomic differences in invention among children with strong early mathematics performance (Bell et al., 2019b) illustrate this unrealized potential. Institutional changes can reach some of it: Dynarski et al. (2021) show that an early guarantee of existing grant aid substantially increases flagship enrollment among high-achieving, low-income students.

To the extent that subsequent changes have reached previously constrained, high-return students, these policies seem likely to have produced larger innovation responses than we might expect from comparable policies today.

6.2 Are the Marginal Innovations Important?

A natural concern with our findings is that the patents induced by expanded loan access may be of low quality—incremental filings that do not represent genuine technological advances. If credit-constrained students disproportionately lack the scientific training or institutional resources to produce high-impact work, then lifting their borrowing limits might simply lower the average quality of the patent pool without generating meaningful social returns. On this view, the welfare case for expanded student loan access would be considerably weaker than the aggregate patent counts suggest.

Table 4 examines whether the patenting response extends to more highly cited work. We re-estimate Equation 3 using progressively more demanding patent quality thresholds: any patent, any patent with at least one subsequent citation, patents in the top quartile of the within-year citation distribution, and patents in the top 5%. A response concentrated in low-citation filings would tend to produce smaller percentage effects at higher thresholds. Conversely, a response that remains visible at higher thresholds would be consistent with the "lost Einsteins" hypothesis that financial barriers impede innovators capable of producing valuable work.

Table 4: Testing the Lost Einsteins Hypothesis for Financial Constraints

	Outcome: Patent Filers per 1,000			
	Any Patent (1)	Cited Patent (2)	Top Quartile (3)	Top 5% (4)
First Year Borrowing ($1,000s)	0.454**	0.330**	0.176*	0.0313
	(0.152)	(0.115)	(0.0697)	(0.0262)
1[Constrained]	−1.169***	−0.734**	−0.315*	−0.0365
	(0.318)	(0.242)	(0.146)	(0.0625)
Cohort Fixed Effects	Yes	Yes	Yes	Yes
Mean of outcome	0.612	0.390	0.193	0.0349
% impact of $1,000 more loans	74%**	85%**	91%*	90%
95% CI for % impact	(26%, 123%)	(27%, 142%)	(20%, 162%)	(−57%, 237%)

Notes: Each column re-estimates the IV specification from Equation 3 using a progressively more selective patent quality threshold as the outcome. Column (1) replicates the main result (any patent filer). Column (2) restricts to patents with at least one subsequent citation. Column (3) restricts to patents in the top quartile of the within-year citation distribution. Column (4) restricts to patents in the top 5%. The % impact row reports the IV coefficient scaled by $1,000 and divided by the mean, expressed as a percentage. Cohort fixed effects included throughout.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Across these thresholds, the point estimates imply percentage responses similar to or larger than that for any patent: the estimated percentage impact of $1,000 in additional loans is 74% for any patent, 85% for cited patents, and 91% for top-quartile patents. The cited and top-quartile estimates are positive and statistically significant at conventional levels, while the top-5% estimate is imprecise and statistically indistinguishable from zero. The persistence of a response among cited and top-quartile patents suggests that the additional innovation is not confined to low-value filings.

This pattern aligns naturally with the "lost Einsteins" hypothesis of Bell et al. (2019b), who document large socioeconomic differences in invention even among children with strong early mathematics performance. Our findings suggest that financial constraints on higher education are one barrier to realizing this potential, and that easing them can foster valuable as well as additional innovation. One economic mechanism consistent with these findings is that the human capital investments enabled by student loans—additional years of schooling, graduate training, and exposure to research environments—are complementary to producing high-quality innovation. Students pursuing education despite binding credit constraints may

have substantial unmet demand for this training. The quality results thus shift the evidence away from an account in which expanded loan access produces mainly marginal, low-value work.

Appendix Tables A1–A3 examine whether the response is concentrated in particular demographic groups or technology fields. Positive point estimates appear across all racial groups examined (White, Black, Hispanic, and Asian inventors) and across all six major technology categories, with the only statistically significant category-level estimate in Mechanical patents (106%). The female point estimate is negative and imprecise, and differences across subgroups are not statistically significant. For readers expecting the innovation response to be confined to a particular technology, the broadly positive pattern across fields offers suggestive evidence of a wider reach. The estimates leave room for heterogeneous responses, but make a broader education-financing mechanism worth considering alongside field-specific explanations.

7 Conclusion

This paper links administrative patent records with consumer credit records and applies a constraint-induced IV design to a new outcome: subsequent patenting. Borrowers classified as constrained by the Stafford limit exhibit increases in borrowing and patenting relative to other borrowers across cohorts exposed to higher limits. The estimates indicate that expanded education financing can increase participation in innovation.

The implied elasticity, normalized by first-year borrowing, is approximately 1.9, with a fairly large 95% confidence interval of 0.67–3.22. These estimates of the effects of loans on future patenting should be interpreted as a LATE, and should be regarded as most internally valid for students impacted by loan changes in the early 2000s; there is reason to believe additional marginal reforms may have more limited impacts today.

A key question is whether the innovations crowded out by financial constraints are genuinely important or merely marginal. The point estimates of percentage responses for highly cited patents are similar to or larger than the response for patenting overall. This pattern suggests that the opportunities unlocked by additional financing include valuable innovation,

consistent with the "lost Einsteins" hypothesis of Bell et al. (2019b). Educational investments enabled by loans may be complementary to producing high-quality work, allowing students with unrealized inventive potential to acquire the training and research experience they need.

A priori, theory offered ambiguous predictions. While debt overhang might push students away from innovative careers—which tend to offer risky payoffs that are not fully captured by the individual—our results suggest that the human capital channel dominates. The evidence is more consistent with a story in which increased access to higher education financing opens pathways to further schooling, with downstream benefits for innovation. One reason students' interest in innovation may be less deterred by debt than prior literature would predict is the optimistic beliefs documented among students in science and technology careers (Ganguli et al., 2022).

What policies can governments use to stimulate innovation? Our findings put education financing alongside research funding and R&D incentives as a potential lever. For comparison, Azoulay et al. (2019) report an elasticity of related private-sector patenting with respect to NIH funding of 0.437, while Dechezleprêtre et al. (2023) report elasticities of firm patenting with respect to policy-induced R&D spending of approximately 0.50–0.65.[8] Our point estimate is larger, though it corresponds to a specific LATE, and the lower end of its confidence interval is close to these more modest responses. A historical pool of talented students held back by financing barriers offers an economic reason for a large response at our margin. Similarly, Dechezleprêtre et al. (2023) emphasize financing constraints in explaining firms' responses to R&D incentives. Comparing fiscal returns additionally requires accounting for cumulative student lending, repayment, and patent output per induced inventor; the elasticity comparisons concern proportional responsiveness.

Patents are also an incomplete metric for either policy. Research funding generates scientific knowledge, training, and local economic activity beyond patenting, just as education financing shapes earnings, occupational choice, and much else beyond invention. Our contribution is evidence on a previously understudied component of that broader accounting:

[8]See Azoulay et al. (2019), Table 8, column 5, and Dechezleprêtre et al. (2023), online Appendix C.3 and Table A6. The latter range is across specifications and uses firm R&D spending, not government tax expenditure, as the input.

the patenting response to expanded education financing at a policy-responsive borrowing margin.

The core finding is that easing binding education-financing constraints can expand participation in American innovation. Students already striving to pursue valuable educational opportunities can respond strongly when financing becomes available. For innovation policy, this directs attention to the educational investments that additional resources would enable, and to the students positioned to undertake them. Reforms that reach such opportunities can generate benefits beyond the students' own earnings.

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8 Appendix

8.1 Supplementary Figures

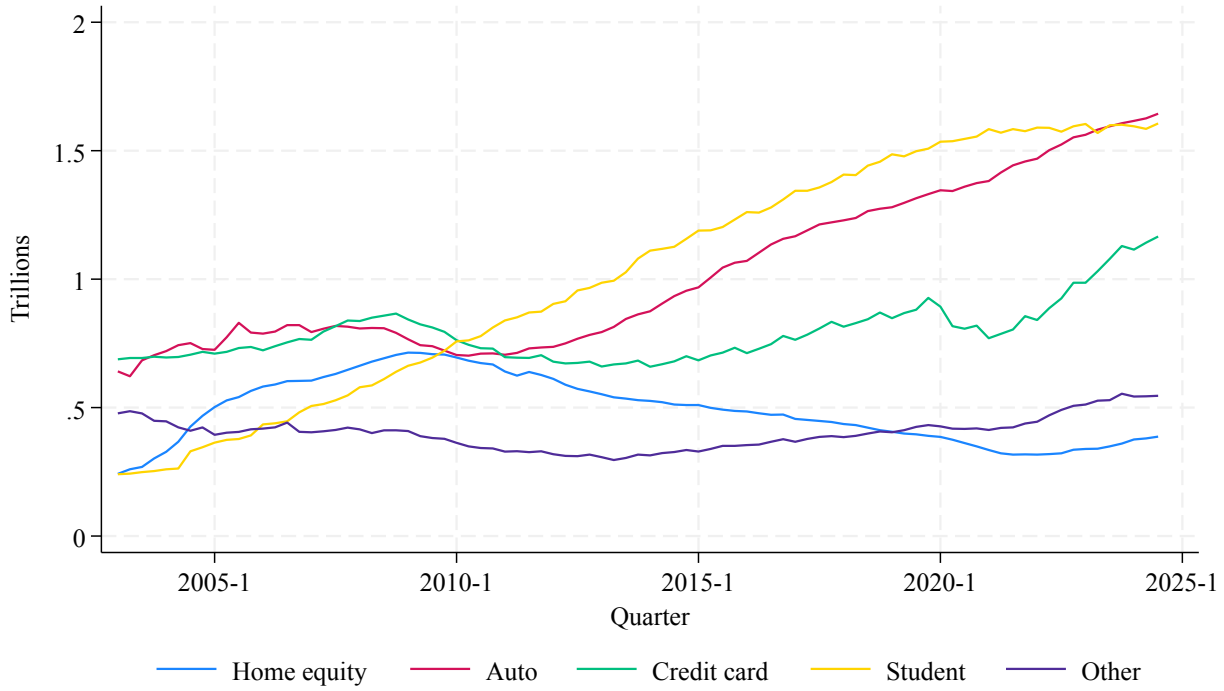


Figure A1: Top forms of debt by quarter (excluding mortgages)

Each line depicts the nominal dollar value of debt over time by each quarter for each major category of debt aside from mortgages from 2003, Quarter 1 to 2024, Quarter 3. Mortgage debt has been excluded. Source: Center for Microeconomic Data (2024)

United States Patent [19]

Johnson

[11] **Patent Number: 4,591,071**

[45] **Date of Patent: May 27, 1986**

[54] **SQUIRT GUN**

[76] Inventor: **Lonnie G. Johnson,** 1463 E. Barkley Dr., Mobile, Ala. 36606

[21] Appl. No.: **541,898**

[22] Filed: **Oct. 14, 1983**

[51] **Int. Cl.**[4] **B67D 5/32**

[52] **U.S. Cl.** ..... **222/39;** 222/79; 222/401; 340/384 E; 340/406; 116/137 R

[58] **Field of Search** ..... 340/384 E, 406; 116/137 R, 139; 222/39, 79, 323, 324, 401

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3,202,318	8/1965	Black	222/39
4,086,589	4/1978	Cieslak et al.	340/384 E
4,214,674	7/1980	Jones et al.	222/401
4,239,129	12/1980	Esposito	222/79

Primary Examiner—H. Grant Skaggs
Attorney, Agent, or Firm—John A. Beehner

[57] **ABSTRACT**

A toy squirt gun which shoots a continuous high velocity stream of water. The squirt gun is configured as a structure facilitating partial filling with water leaving a void for compressed air. The squirt gun includes a nozzle for ejecting water at high velocity, a pressurization pump for compressing air into the gun to pressurize water contained therein, and a trigger actuated flow control valve for shooting the gun by controlling flow of pressurized water through the nozzle. A battery-powered oscillator circuit and a water flow powered sound generator produce futuristic space ray gun sound effects when the gun is shooting.

9 Claims, 7 Drawing Figures

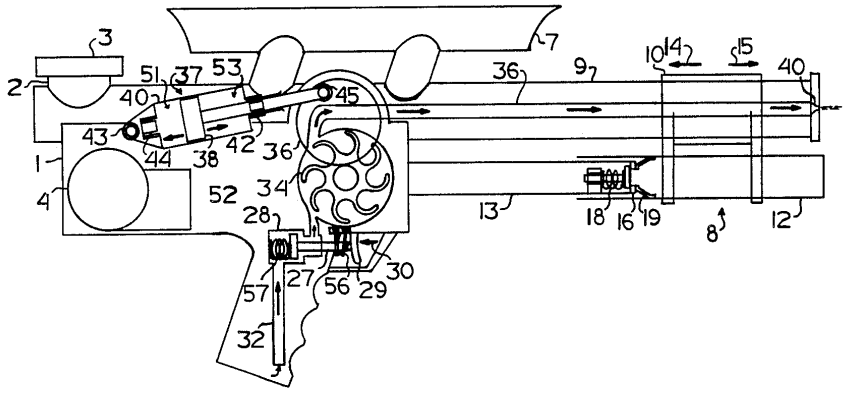


Figure A2: Example of a granted patent

8.2 Heterogeneity

Table A1: Heterogeneity by Gender

	Outcome: Patent Filers per 1,000		
	Main	Male	Female
	(1)	(2)	(3)
First Year Borrowing ($1,000s)	0.454**	0.819*	−0.0483
	(0.152)	(0.331)	(0.127)
1[Constrained]	−1.169***	−2.309***	0.198
	(0.318)	(0.726)	(0.265)
Cohort Fixed Effects	Yes	Yes	Yes
Mean of outcome	0.612	0.786	0.232
% impact of $1,000 loans	74%**	104%*	−21%
95% CI	(26%, 123%)	(22%, 187%)	(−128%, 86%)

Notes: Re-estimates the IV specification from Equation 3 on subsamples defined by imputed inventor gender. Column (1) reproduces the main pooled estimate for reference. Gender is imputed using name-based methods. The difference between male and female estimates is not statistically significant. Cohort fixed effects included throughout.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Heterogeneity by Race

	Outcome: Patent Filers per 1,000				
	Main	White	Black	Hispanic	Asian
	(1)	(2)	(3)	(4)	(5)
First Year Borrowing ($1,000s)	0.454**	0.650**	0.387	0.176	0.740
	(0.152)	(0.240)	(0.475)	(0.182)	(0.628)
1[Constrained]	−1.169***	−1.547***	−1.365	−0.424	−1.957
	(0.318)	(0.469)	(0.899)	(0.414)	(1.438)
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of outcome	0.612	0.844	0.559	0.369	0.653
% impact of $1,000 loans	74%**	77%**	69%	48%	113%
95% CI	(26%, 123%)	(21%, 133%)	(−97%, 236%)	(−49%, 144%)	(−75%, 302%)

Notes: Re-estimates the IV specification from Equation 3 on subsamples defined by imputed inventor race. Column (1) reproduces the main pooled estimate for reference. Race is imputed using name-based and geography-based methods. Differences across racial groups are not statistically significant. Cohort fixed effects included throughout. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Heterogeneity by Technology Category

	Outcome: Patent Filers per 1,000					
	Chemical (1)	Comp. & Comm. (2)	Drugs & Medical (3)	Elec. & Electronic (4)	Mechanical (5)	Design/Plant (6)
First Year Borrowing ($1,000s)	0.0570	0.0483	0.0586	0.0359	0.0810*	0.0330
	(0.0493)	(0.0665)	(0.0658)	(0.0587)	(0.0348)	(0.0268)
1[Constrained]	−0.170	−0.170	−0.267*	−0.0793	−0.106	−0.0370
	(0.0991)	(0.124)	(0.130)	(0.128)	(0.0822)	(0.0637)
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean of outcome	0.0476	0.117	0.0602	0.0824	0.0761	0.0380
% impact of $1,000 loans	120%	41%	97%	44%	106%*	87%
95% CI	(−83%, 323%)	(−70%, 153%)	(−117%, 312%)	(−96%, 183%)	(17%, 196%)	(−51%, 225%)

Notes: Re-estimates the IV specification from Equation 3 using patent filings in each technology category as the outcome. Technology categories follow the NBER patent classification. The only statistically significant effect is in Mechanical patents; differences across categories are not statistically significant. Cohort fixed effects included throughout. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8.3 Match Appendix

In order to match our patent data to the UC-CCP, we undergo an anonymized "hashed merge" process. The patent data were systematically linked to the CCP records by employing a standardized name-matching process similar to that of Bell et al. (2019b). Initially, all names were converted to lowercase and assigned a match priority of 1. Any subsequent modifications to a name resulted in the creation of a new observation, with the match priority incremented by one. Excessive spaces within names were identified and removed. Furthermore, all non-Latin alphabet characters and punctuation marks were eliminated. Extraneous information, such as "(Deceased)", "(Owner)", "(Esq)", "(Real Party in Interest)", "(patentee/owner)", and "(3rd Party Rq.)", was also removed. Honorifics were stripped from names, specifically if "PhD", "JD", "MBA", or "PE" appeared at the end of a name. In cases where nicknames were indicated by parentheses or "aka", the nickname was initially used to replace the given first name; subsequently, these nicknames were removed. Suffixes, which occasionally appeared at the end of first, middle, or last name fields, were extracted if they included "JR", "SR", "1st" through "5th", or numerals I-V, and were stored separately from the name. The sequence of these edits, while not necessarily aligned with the "match priority" variable if each round did not yield an edit, was as follows: names were converted to lowercase, spaces were removed, punctuation was eliminated, extraneous information was discarded, honorifics were stripped, nicknames were processed, and suffixes were extracted and stored separately. For city and state data, all entries were converted to lowercase. Additionally, it was ensured that the entries were within the United States or that the inventor region code corresponded to one of the 51 states plus the District of Columbia.