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Lost in Transition: Financial barriers to new technologies

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Abstract

Advanced economies are reshaped by transitions from old to new technological paradigms. These transitions rely on complementary innovations that spread new technologies across industries. What happens when a financial crisis disrupts investment in these innovations? Using a Schumpeterian endogenous growth model with financial frictions, we show that investment in new technologies is more sensitive to tighter financial conditions than investment in mature technologies. The key mechanism is path dependence: firms build expertise in the technologies they previously developed, leading young firms to self-select into emerging technologies. As young firms are more financially constrained, shocks to financing disproportionately depress innovation in new technologies. We validate this mechanism using causal evidence on green patenting by German firms around the Global Financial Crisis. The aggregate fraction of patenting in carbon reducing technologies stagnated after the crisis. Quantifying our model using the causal estimates from the micro data implies that the slowdown of the sorting of young firms into new technologies accounts for about a fifth of the macro trends in such green innovation.

Keywords: Endogenous Growth, Technological Progress, Climate Change, Financial Frictions, Innovation, Creative Destruction.

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1. Introduction

Modern economies are frequently reshaped by technological transitions in which new paradigms of production gradually replace old ones. Examples include the transition from the typewriter to the computer, from steam power to electricity, and from the internal combustion engine to the electric vehicle. These episodes of structural change can be set in motion by general purpose technologies, shifts in consumer demand, or policy interventions, but their success ultimately depends on whether the new technology can be adapted to a wide range of uses and production processes. That, in turn, requires a sustained flow of complementary innovations that improve the technology, lower its costs, and enable its diffusion across firms and industries (Griliches 1957, Bresnahan and Trajtenberg 1995, Acemoglu et al. 2016, Ribeiro 2026). A natural concern is that disruptions to investment in these complementary innovations may be especially costly, because they slow the reallocation of economic activity toward new technologies.

This paper argues that tighter financial constraints—such as those induced by a financial crisis—disproportionately depress innovation in new technologies during such transitions. Our mechanism is *not* that new technologies are inherently harder to finance than mature technologies. Rather, it is because the financial crisis disproportionately hurts the kind of firms most active in the transition, namely younger, start-up firms. This rests on two forces. First, innovation is path dependent across technology vintages at the firm level: firms find it cheaper to continue innovating within the technology vintage in which they have previously succeeded. Early in a transition, younger firms therefore self-select into innovation in emerging technologies, while older firms are more likely to innovate in the mature technologies with which they are familiar. Second, younger firms are generally more financially constrained than older firms, because they have not yet developed the lending relationships or securities-market access of mature firms (Gertler and Gilchrist 1994, Cloyne et al. 2023). Taken together, a tightening of financial conditions disproportionately depresses innovation in new technologies by mostly affecting the firms that select into them. The costs of financial crises are therefore *state dependent*: they are especially large early in a transition, when young firms play a central role in the diffusion of the new technology.

We analyze the effect of the self-selection of young firms into new technologies on the susceptibility to financial shocks in three steps. To motivate our main argument, we use global patent data to provide empirical evidence on three stylized innovation facts from before, during, and after the Global Financial Crisis. First, we find that there is a clear positive relationship between the age of technologies and the age of innovators: the younger a technology, the greater the fraction of patents originating from young firms. Second, innovation by young firms was disproportionately affected by the Global Financial Crisis. Third, we examine several case studies where we can clearly distinguish a transition from a mature to a new technology, we show that the Global Financial Crisis slowed or reversed the growth of these emerging technologies.

Together, these three facts suggest that financial disruptions can derail technological transitions because the firms that drive early innovation in new technologies are the ones exposed to tight credit.

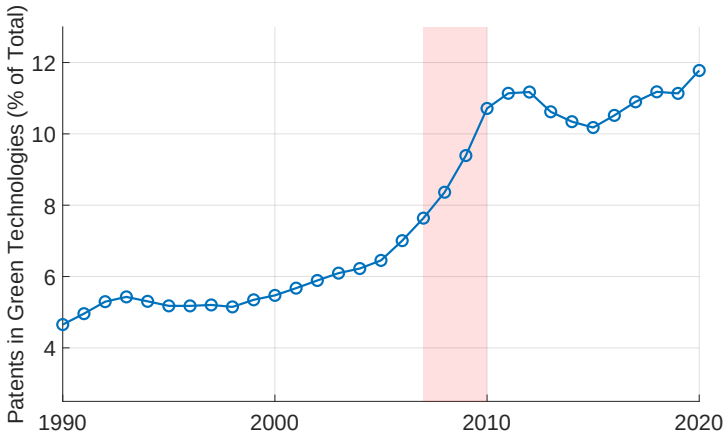
In the second part of the analysis, we formalize the argument in a model of firm dynamics and creative destruction in the spirit of Klette and Kortum (2004), where long-run growth is driven by firms developing higher-quality versions of goods that other firms initially produce. We depart from the standard framework in two main respects: innovation is directed across technology vintages, and R&D is financed subject to an earnings-based constraint. First, any good can be produced with either a modern or an old technology vintage, and these vintages differ in their marginal costs. When firms innovate they decide how much of their research and development (R&D) to direct towards old versus new vintages, respectively To model this choice, we propose a portfolio-dependent R&D technology that distinguishes the cost of expanding innovation from the cost of redirecting it across technological vintages. Firms accumulate innovation expertise through their existing products, which lowers the relative cost of further innovation in the same vintage. As a result, innovation exhibits path-dependence: the higher the number of products that a firm already produces using the older vintage, the lower the cost of further innovation in the old vintage (and vice versa for the newer vintage). This yields that total new vintage innovation is a function of both the profitability of producing with the new vintage and the fraction of the economy's products that is already produced in the new vintage. Second, firms in our model are subject to a simple credit constraint: they are only able to finance R&D up to a firm-specific multiple of their earnings (Drechsel 2023, Lian and Ma 2021). The multiple increases stochastically as firms mature and build a reputation (e.g., a track record of repayment). This makes younger firms' innovation more sensitive to overall credit conditions than the innovation of mature firms.

In the third part of the analysis, we apply our framework to understand the contribution of tight credit and the self-selection of young firms into new technologies to the recent slowdown of *green innovation*. Green innovation is a prime example of an emerging technology in transition. Prior to the 2008-2009 Global Financial Crisis, there was a steady switch of patenting towards technologies related to climate change mitigation (Figure 1). The share of high-quality patents (as measured by innovations that were granted in two or countries) rose steadily from just over 4% to around 11%. That rise juddered to a halt after the financial crisis, and green innovation hovered at around 10 to 11% for the decade that followed.[1] It was not until 2020 that the green patenting share exceeded its crisis peak.

We perform two complementary analyses to show that our proposed mechanism explains a significant share of the slowdown of green innovation. First, we provide a causal validation of the key mechanisms in our model using micro data on patenting (both green and non-green) and firm-bank links for a panel of German firms before and after the Global Financial

[1]The stagnation occurred just after the financial crisis in 2010, which is plausible because of the lag between a fall in R&D and subsequent patenting.

Figure 1. Global Trend: Green Patents as a Percentage of Total Patents



Notes: The figure shows the annual share of patent families classified as green under the Y02 classification of climate-change mitigation and adaptation technologies. Patent records originate from national and regional patent offices and are accessed through Google Patents Public Data. A simple patent family groups publications sharing the same priority claims. Each family is counted once, dated by its earliest filing year, and classified as green if at least one member has a Y02 code. The sample includes invention-patent families with published filings at two or more distinct patent offices and at least one granted member. PCT publications are not counted as an additional patent office. Appendix B, Figure B1, reports robustness checks using triadic families, including families granted at the European Patent Office (EPO), US Patent and Trademark Office (USPTO), and Japan Patent Office (JPO); weighting families by the number of distinct citing families within five years of their earliest filing; restricting the sample to families with an assignee located in an OECD country, using membership as of 2020; and including single-office families. Additional country-level comparisons distinguish attribution by inventor residence, assignee residence, and patent office.

Crisis. Second, we use the micro data to discipline the parameters of the Schumpeterian model, and plot the effect of a financial tightening calibrated to the one observed in Germany after the Global Financial Crisis, in order to quantify the extent to which the self-selection of young firms into new technologies can explain the aggregate slowdown of green patenting.

The micro analysis uses data on German firms for which we observe exposure to the credit-supply contraction of a large bank, Commerzbank. Although innovation is not just directly financed through bank borrowing, variation in firms' pre-crisis bank relationships provides a useful difference-in-differences design for identifying the effect of tighter credit on subsequent patenting, following Chodorow-Reich (2014) and Huber (2018). This design differences out common post-crisis changes in the profitability of green innovation—such as changes in policy support, energy prices, or investor demand—and isolates the differential effect of tighter credit on more exposed firms.[2] We show that firms more exposed to the contraction in credit reduced patenting only in green technologies. The reason is not that exposed firms selectively cut green innovation. Rather, the effect is entirely driven by younger firms, which reduce both green and non-green innovation by similar magnitudes, while older firms' innovation not damaged. Since younger firms accounted for a disproportionate share of green innovation before the crisis, the overall decline in green patenting among

[2] It is well-known that bank loans are not the main source of finance for innovation (Brown et al. 2009; Hall and Lerner 2010). We use the bank-lending shock not because it is the dominant channel, but because pre-crisis Commerzbank relationships generate sharp, plausibly exogenous differences in credit exposure across otherwise similar firms, enabling a causal validation of our model's mechanisms. Kochen (2025) shows that the ability of firms with greater exposure to Commerzbank to replace lower debt with greater equity was limited.

exposed firms reflects the self-selection of young firms into innovation in the emerging green technology, as predicted by the model.

Quantitatively, the model implies that the self-selection of young firms into new technologies accounts for a meaningful part of the slowdown in green patenting after the Global Financial Crisis. To show this, we calibrate the model to match the German micro data and simulate a financial crisis that arrives while the economy is in transition from a steady state in which most production is non-green to one in which most production is green. In either steady state, the crisis affects green and non-green innovation equally, because green and non-green innovators have the same age distribution. During the transition, however, green innovators are younger, so that a financial crisis hits them harder. When we calibrate the path of credit conditions to the post-2008 decline in credit supply implied by the European Central Bank's Lending Supply Indicator (Altavilla et al., 2019), the mechanism explains about 21% of the slowdown in green patenting.[3] Because forgone green innovations accumulate, this shortfall in patenting delays the green transition in production by close to five years. Finally, we illustrate the state-dependence of these effects by showing that the loss in green patenting would have been reduced by a fifth if the crisis had arrived 10 years later, as green innovators would have had time to mature.

Related Literature This paper relates to several strands of literature. Our theoretical exercise combines models where innovative technologies arrive in vintages (e.g. Bresnahan and Trajtenberg 1995, Acemoglu et al. 2016, Ribeiro 2026) with models where financial frictions impede optimal innovation decisions (e.g. King and Levine 1993, Rajan and Zingales 1998, Aghion et al. 2018, and more recently Akcigit et al. 2026).

A related literature particularly focuses on financial crises. Garcia-Macia (2017) explains that firms are unable to fund investment in intangible assets during financial crises, as their collateral value is hard to collect. Similarly, the models in Ates and Saffie (2013, 2021) claim that financial turmoil affects technological progress through lowering the ability of banks to observe project quality under imperfect information. In Queraltó (2020), financial crises increase the costs of financial intermediation through balance sheet deterioration á la Gertler and Kiyotaki (2010), which reduces the entrepreneurial entry. Schmitz (2021) adds that the effect of a crisis on innovation is amplified by the fact that small and young firms are most affected by credit tightness, as these produce more radical innovation.[4] We contribute to this

[3] Many other forces shaped green innovation after 2008 and are held fixed in the model, including fiscal policy and the cuts to green subsidies under austerity, the rise of shale gas (Acemoglu et al. 2023) and the fall in energy prices after 2007, and shifts in investor demand for green assets (see, e.g., Hofman and Huisman, 2012). The exercise isolates the contribution of tighter credit operating through the self-selection of young firms; it does not aim to account for the full decline.

[4] Crouzet et al. (2026) provide a complementary organizational explanation for the role of young firms in technological transitions. They show that young firms have an advantage in implementing new technologies when these require changes in occupational workstyles that conflict with incumbents' established organizational practices. Their mechanism complements the technological path dependence emphasized here. For related work on firm age and the distinction between incremental and more novel or radical innovation, see Loderer et al. (2017), Akcigit and Kerr (2018a), and Ewens and Marx (2024).

literature by looking at the effect of credit constraints on the direction – modern versus old –of innovation, in younger versus mature firms, and from there at the overall effects of credit tightening on the speed of a transition toward modern production technologies. In doing so, we also contribute to the understanding of why financial crises appear to have much more persistent effects on output than non-financial recessions in the data (see, e.g., Cerra and Saxena 2008, Reinhart and Rogoff 2014, Duval et al. 2020).

The key assumption in our model that young firms face greater financial constraints is rooted in a long literature (Arrow (1962)). Gertler and Gilchrist (1994) note that informational frictions in finance are particularly strong for young firms. This is because young firms have yet to establish a sufficiently long credit history, as pointed out by (e.g.) Evans and Jovanovic (1989), Haltiwanger et al. (2013), Davis and Haltiwanger (2024) and Chaney et al. (2012). Recent evidence supports this idea. Cloyne et al. (2023) find that young firms' investments are more responsive to monetary policy shocks, a result confirmed for employment by Bahaj et al. (2022). Clymo and Rozsypal (2022) similarly find that young firms exhibit more business cycle sensitivity, consistent with tighter financial constraints.

Our application to green patenting during the Global Financial Crisis is closest to the literature that jointly studies endogenous technological change and the transition to clean production. The seminal reference is Acemoglu et al. (2016). Our key novelty is that we introduce a path dependence that ties the economy's capacity to engage in green innovation to the prevalence of green production. This causes green innovation to concentrate among young firms in the transition, which in turn drives its sensitivity to tight credit.

More broadly, the application contributes to the literature that analyzes the interaction between climate and directed technological change after Acemoglu et al. (2012).[5] Existing work in this literature primarily focuses on how policy can induce an optimal transition to clean production (see, e.g., Hémous 2016, Aghion et al. 2016, Fried 2018, Popp 2002 and Newell et al. 1999). Hémous and Olsen (2021) and Dugoua and Moscona (2026) provide recent reviews. We contribute to this literature by introducing credit constraints and firm dynamics, looking at how credit tightening can slow down the transition of the overall economy towards a clean economy by directly affecting green innovation by younger and smaller firms.

We consider our theoretical exercise complementary to papers that explain why clean technology adoption might be difficult for financially constraint firms. Lanteri and Rampini (2025), for example, show that older shipping firms were more likely to adopt clean technologies in 2022 than younger firms, and rationalize this with a model in which green adoption comes at high up-front costs. Capelle et al. (2025) show formally that investments by that financially constrained firms have a pecking order, where they first choose to invest in cheaper (polluting) capital. Our application is different in the sense that we focus on green *innovation* rather than green capital *adoption*. In addition, our contribution is that even in absence of

[5]This work, in turn, builds on the long literature on growth and climate change, starting with Nordhaus (1994). See Golosov et al. (2014) and the recent reviews by Caggese et al. (2025) and Hassler et al. (2018).

any innate difference in the cost of financing green or dirty innovation, green innovation is endogenously more sensitive to financial constraints when the economy is in transition.

Our micro data analysis relates to the recent literature on the financial costs of climate change and on green finance. Bolton et al. (2022) show that financiers require compensation for climate risk. Our focus is instead on how finance – or the lack of it – affects firms' choice to innovate green versus dirty, and from there the steady state firm-size distribution and aggregate growth and welfare. We also relate to De Haas et al. (2025), who show that firms that were rejected from a loan application were less likely to adopt green management technologies and to invest in green practices. De Haas and Popov (2023) find that industries in countries with better-developed financial systems transition faster to the use of low-carbon production technologies. Our contribution over and above these papers is to demonstrate that green innovations were particularly hampered by the Global Financial Crisis because they were an example of an emerging technology.[6]

Finally, our empirical strategy builds on work that identifies the real effects of financial tightness by exploiting variation in the lenders that firms rely on. Examples include Chodorow-Reich (2014), Acharya et al. (2018), Bentolila et al. (2018), Franklin et al. (2020) and Giroud and Mueller (2017), who analyze the employment effects of tightening of credit supply using variation in firm-level exposure. It is similarly related to Almeida et al. (2012), Greenstone et al. (2020), Adelino et al. (2015), Aghion et al. (2021), Paravisini et al. (2015), and De Ridder (2019). These papers use exposure to credit shocks to analyze the effect on employment, investments, exports, output and patenting. To our knowledge, ours is the first paper to use that methodology to study the differential effect of tight credit on (non) green patenting.[7]

Outline The remainder of this paper proceeds as follows. We provide the motivating evidence on the stylized facts of patenting around the Global Financial Crisis in Section 2. The Schumpterian growth model with path dependence and financial constraints is presented in Section 3. The causal evidence in support of the model's mechanisms and the quantitative application to green innovation are presented in Section 4. Section 5 concludes.

[6] A related literature notes that there has recently been a dramatic rise in "green investors": investors that allocate a large fraction of their capital to climate-change related projects. Bolton and Kacperczyk (2021) show that low-emission firms have lower expected returns on U.S. capital markets, implying that their valuations are higher and cost of capital are lower. Berk and van Binsbergen (2025) finds that the impact of green investors on cost of capital remains small. Gormsen et al. (2024) argue that the green wedge in capital costs has increased rapidly between 2016 and 2022. Accetturo et al. (2024) and Oliviero et al. (2025) show that green investments are responsive to changes in credit supply, consistent with our findings. Patozi (2023) notes that green investors might affect monetary policy transmission. A review on the interaction between climate change and finance is provided in Giglio et al. (2021).

[7] Two contemporaneous papers study the response of green innovation to macroeconomic and financial shocks. Känzig et al. (2026) find that green innovation is countercyclical, which they explain through its greater dependence on distant profits. Fornaro et al. (2026) find that tighter financial conditions disproportionately reduce R&D by specialized green innovators, which are younger and more dependent on external finance, consistent with what we find. Our analysis complements this work by isolating the effect of a bank-credit supply shock and examining how the interaction between firms' technological experience and financial maturity shapes the direction of innovation at different stages of a technological transition.

2. Innovation During Technological Transitions

To motivate the analysis, we start by looking at how patenting evolved in various key emerging technologies around the Global Financial Crisis. As shown in Figure 1, the steady rise in the share of green patenting came to a temporary halt after the Global Financial Crisis. This pattern is not restricted to clean technologies: a similar slowdown can be seen in several other emerging technologies, spanning different fields.

Figure 2 illustrates that fact by plotting the share of patenting in eight emerging technologies, ranging from from electric vehicles and solar photovoltaics to biotechnology and communications. For each of these technologies we calculate the share of patenting in the emerging technology relative to the sum of patenting in the emerging technology and the established technology that it replaces.[8] The subfigures are alphabetically ordered.

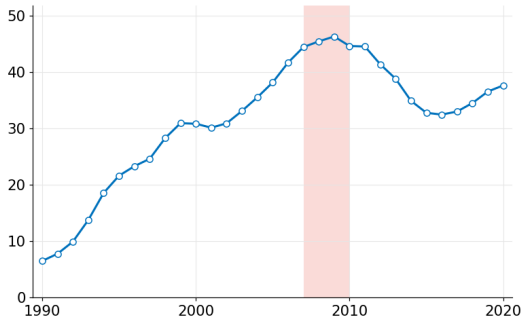
Consider, for example, long-distance data transmission (panel c). In the early 2000s, fiber-optic networks largely relied on systems that detected changes in the intensity of light to recover information. As internet traffic expanded, these conventional transmission systems faced increasing limits on how much data they could carry. Coherent optical transmission, already under development in the 1990s, offered a way to overcome these limits. Advances in optical receivers and digital signal processing allowed these systems to exploit additional properties of light, including its phase, and transmit much more data through existing fiber cables. These advances supported their progressive adoption in long-distance networks during the following decade. The corresponding patenting share increased before and during the crisis, stagnated in the early 2010s, and resumed growing toward the end of our sample.

The extent and persistence of the slowdown vary across examples. The share of biotechnology (i.e. patenting in genetically modified organisms) in agricultural patenting, was sharply rising before the financial crisis, peaked in 2009, and subsequently declined (panel a). A similar pattern is visible in iPSC Stem-cell technologies in tissue patents (panel g). Peer-to-peer networking and turbocharging (panels d and h) exhibit prolonged increases followed by a flattening of their shares after the crisis. Electric vehicles and Solar photovoltaic modules (panels b and f) stagnated post crisis, but eventually started to grow again by the end of our sample period. The share of self-driving technologies in overall vehicle hardware (panel e) only saw a modest at a reduced growth rate, before returning to pre-crisis growth.

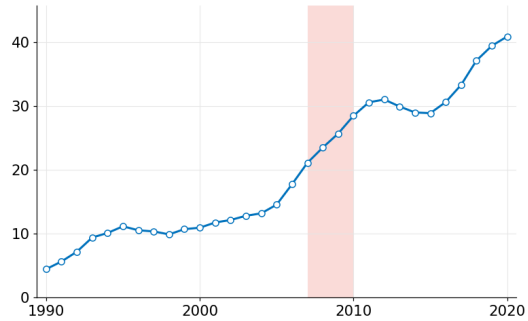
These examples are reflections of the broader pattern that emerging technologies fell behind trend during the crisis. There are exceptions, of course, but systematically performing the analysis in Figure 2 for all technologies is difficult because each emerging technology would have to be matched to the older technology it replaces. To provide broader evidence of the pattern, Appendix B.3 shows that young technologies on average fall further behind their predicted patenting path in the aftermath of the crisis. The appendix also shows that such a shortfall for young technologies arises whenever financial conditions tighten, for example during the Volcker disinflation in the early 1980s, and not when financial conditions are slack.

[8] Appendix B.2 details how we construct the technology pairs using Cooperative Patent Classification codes.

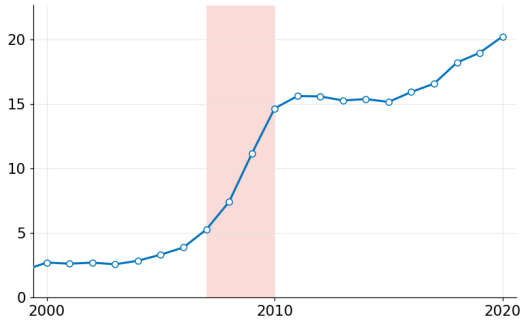
Figure 2. Examples of Patent Shares of Eight Emerging Technologies



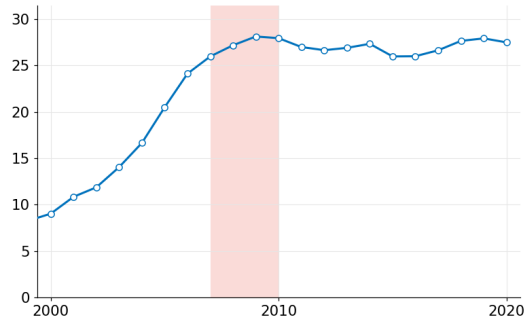
(a) Biotech in Agriculture



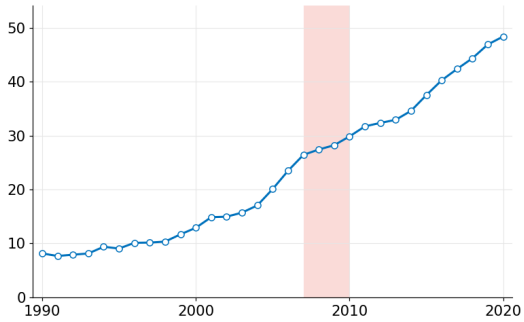
(b) Electric Vehicles in All Vehicle Propulsion



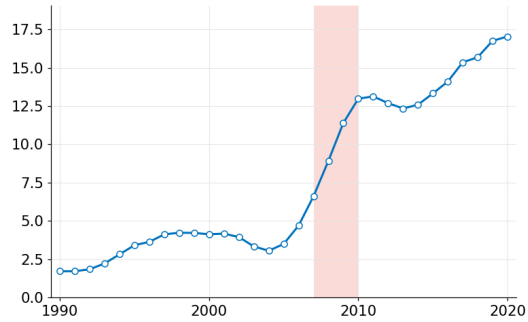
(c) Optic Fibre in Data Transmission



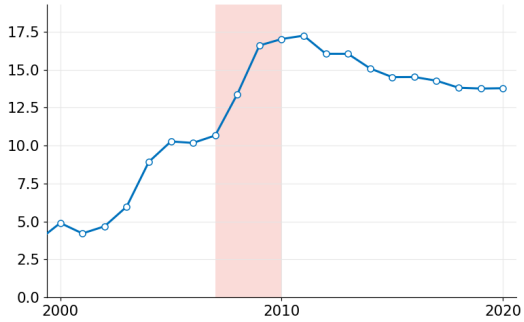
(d) Peer-to-Peer in Server Models



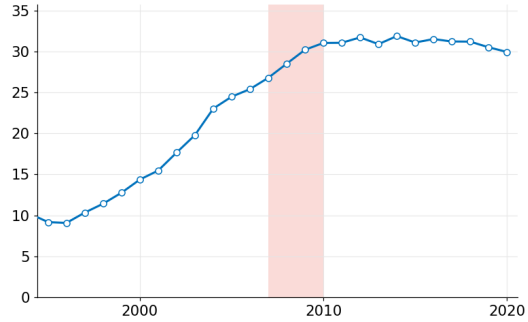
(e) Self-Driving Tech in Vehicle Hardware



(f) Solar PV in Power Generation



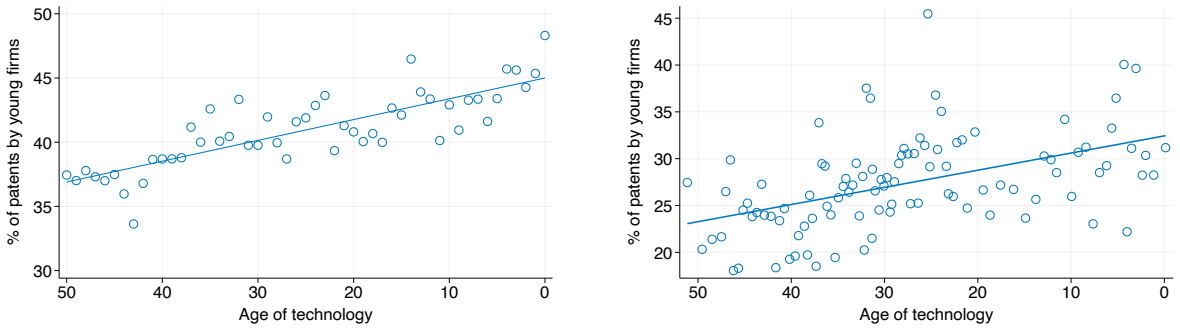
(g) Stem cells (iPSC) in Organic Tissue



(h) Turbocharging in Engine Technologies

Notes: Each panel plots the patent share of an emerging technology over the sum of the emerging technology plus the corresponding established technology (see Table B2 for definitions and Appendix B.2 for details). The shaded band marks the 2007–2010 period.

Figure 3. Technology Age and Share of Young Firms



(a) Without year fixed effects

(b) With year fixed effects

Notes: The figure plots the relationship between technology age and the share of patents from young firms in a technology-year panel. Technologies are defined at the four-digit CPC level and the sample covers 1990–2006. Observations are grouped by technology age into 50 distinct age bins (technologies 50 years old or more are in the 50 bin), each showing the mean young-firm patenting share. The two panels use the same sample of 1,568 technology–year observations, covering 99 CPC subclasses and 33,482 distinct assignees over 1990–2008.

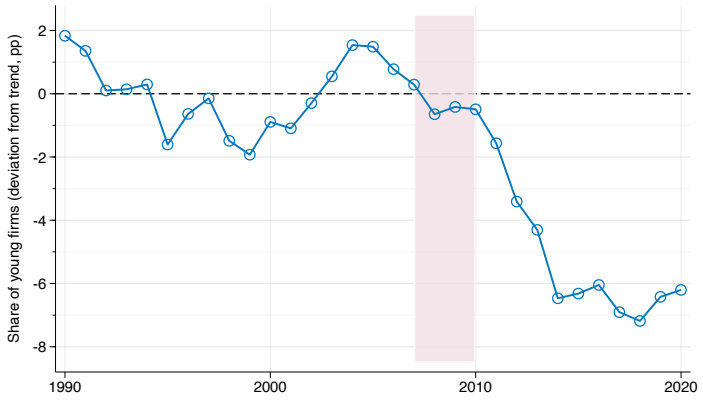
What explains the larger effect of financial disruptions on innovation in emerging technologies? Our argument in the next section is that innovation is path dependent: firms find it cheaper to innovate in technologies in which they have previously succeeded. This gives young firms an important role in emerging technologies, while older firms tend to continue innovating in more established ones. If younger firms are also more sensitive to a tightening of financial conditions, such a crisis will disproportionately affect innovation in new technologies, even when there is no intrinsic difference in their financing costs. While the strength of these forces may vary sizably across technologies, we show that, on average, patent data exhibit the two patterns at the heart of this mechanism.

First, younger firms contribute disproportionately to innovation in emerging technologies. To show this, we measure firm age by the number of years since its first patent, and classify a firm as young if it filed its first patent within the previous ten years.[9] The age of a technology equals the number of years since it first recorded at least 20 patents in a single year.[10] To identify technologies, we use the Cooperative Patent Classification (CPC) codes assigned to each patent. We retain inventional CPC codes, which capture the patent's core inventive content, and define technologies at the four-digit CPC level. This procedure yields 130 technologies with initial transitions after 1990.

[9] Patent and assignee information comes from PatentsView. We exclude patents without an assignee or whose assignee is not a private business. Because foreign firms may patent in other jurisdictions before appearing in USPTO data, the analysis of firm age is restricted to US-based assignees. Our data start in 1976 and the analysis of firm age begins in 1990. The resulting sample contains 3.2 million patents filed by 0.2 million assignees, of which 43% are classified as young at the time of filing. The measure refers to years since a firm's first observed patent, which may differ from its age since founding. Nothing hinges on the exact cut-off year being ten to define young.

[10] The stylized fact that young firms innovate disproportionately in young technologies is robust to alternative thresholds for defining technology age. We require a minimum number of patents in a single year because some technologies exhibit negligible patent counts in scattered early years, whereas once a technology experiences a burst of patenting, its presence in the data usually becomes sustained.

Figure 5. Share of Patents from Young Firms



Notes: In year t, a firm is classified as young if the filing year of its first observed patent, t_0, satisfies $t - t_0 \leq 10$. The sample includes granted USPTO patents with a US-based assignee. The series is shown in deviation from a linear trend estimated over 1990–2006.

Figure 3 plots the fraction of patents in a technology that originate from young firms against the number of years since that technology first crossed the threshold of 20 patents. The horizontal axis is reversed, so younger technologies are on the right. We use observations from 1990 to 2006 to abstract from the effects of the Global Financial Crisis. Younger technologies have a larger fraction of patents from young firms. In the left panel, each additional year of technology age is associated with a decline of 0.14 percentage points (standard error 0.07) in the fraction of patents from young firms. The left-hand panel (a) shows the relationship without controls, while the right-hand panel (b) controls for year fixed effects to account for changes in the aggregate share of patenting by young firms. The inclusion of year effects leaves the slope of the relationship approximately unchanged. The relationship is an average one: it does not imply that every emerging technology depends equally on young firms.

Second, we show that, on average, young firms' contribution to aggregate innovation fell markedly after the Global Financial Crisis. Figure 5 shows how young firms' share of aggregate patenting evolved around the crisis. It plots this share between 1990 and 2020, in deviation from a linear trend estimated over 1990–2006.[11] Following the crisis, the share of patenting by young firms declined by around seven percentage points relative to its pre-crisis trend. In the underlying series, their share fell from about 40% to 33% (note this is a decline in their contribution to total patenting, not their absolute number of patents). The decline cannot be simply accounted for by the secular fall in the total share of young US firms documented by Decker et al. (2016). Appendix Figure B3 compares young firms' patenting share with their shares of the number of firms and of employment, after removing pre-crisis trends. Neither of the latter series exhibits a comparable decline around the crisis.

[11] The results are qualitatively robust to alternative adjustments for pre-crisis time trends, including higher-order polynomials. Even without any de-trending there is a substantial fall: from 39% in 2007 to 33% in 2017.

These two patterns provide a potential explanation for the evolution of emerging technologies documented above. Young firms are disproportionately represented in emerging technologies and accounted for a smaller share of patenting than we would expect after the Global Financial Crisis. If path dependence leads young firms to select into new technologies, and financial tightening has a greater effect on young firms, innovation in new technologies will be disproportionately exposed to financial disruptions. These aggregate patterns are suggestive of the proposed mechanism but in the next section, we formalize it in a model of innovation with path dependence and financial constraints. We then turn to more precise firm-level data to test the mechanism and quantify its importance for the slowdown in green innovation.

3. Framework

We analyze an economy in which there are two vintages of technologies: an old and a new technology vintage. Our goal is to quantitatively study the economy's transitional dynamics after a shock to the relative profitability of producing with the new vintage, and the effect of a temporary tightening of financial conditions in the middle of that transition. In this section, we start by setting up the economy and describing the properties of the economy along an initial balanced growth path, where production with the new technology vintage is still expensive. We then explain that early in a transition, induced by a decline in the cost of producing with the new technology vintage, young firms are responsible for a large share of innovation in the new technology. In Section 4 we test that production, and show that a simulated financial tightening disproportionately affects the modern technology as a result.

3.1. Preferences

The economy comprises of a continuum of identical households with unit mass that choose the path of consumption to maximize utility along:

$$U = \int_0^\infty \exp(-\rho t) \ln C_t \, dt$$

where C_t denotes consumption and ρ denotes the discount rate. The household supplies a single unit of labor inelastically. Time is continuous and indexed by t, which we suppress when convenient. Consumption is a Cobb-Douglas aggregate of a continuum of intermediate goods of measure 1. Each good j can be produced by any firm i in the set of firms I_j that owns a patent to a production method to produce that good. The intermediate goods are competitively aggregated along:

$$Y = \exp \int_0^1 \left(\ln \sum_{i \in I_j} q_{ij} y_{ij} \right) dj.$$

where $Y = C$ is aggregate output, which is fully consumed. y_{ij} is the amount of good j that is produced by firm i, and q_{ij} denotes the quality of the patent that firm i owns. Higher quality patents enable firms to produce goods from which the consumer derives more utility per unit. Beyond differences in quality, the output of good j of the various producers is perfectly substitutable for the consumer, and firms compete on prices. Consumers will thus only demand the good produced by the firm that offers the lowest quality-adjusted price p_{ij}/q_{ij}.

3.2. Production

Goods can be produced with either a modern or an old technology vintage. These vintages determine the marginal cost of producing a good. Whether firm i produces good j with the modern or the old technology is determined by its patent: the production method q_{ij} either enables it to do so with one of the two. The production function associated with producing a good using technology vintage h, where $h \in \{m, o\}$ for modern and old, $y_{ij} = l_{ij} a^h$. Labor l_{ij} is remunerated at the wage rate w, which the firm takes as given. Normalizing the productivity of the old technology vintage to unity, $a^m > 0$ determines the relative marginal cost of producing with either technology:

$$mc^h = \begin{cases} w/a^m & \text{if } h = m \\ w & \text{if } h = o \end{cases}$$

We think of the transition as being driven by an exogenous change in the relative productivity of the modern vintage: while a^m may initially be (substantially) smaller than unity, at some point it becomes cheaper to produce goods with the modern vintage, meaning a^m rises above one.

In the context of a green transition, the drivers of a^m could include taxes and subsidies. In Acemoglu et al. (2016), for example, firms produce with patents that enable them to produce with either a clean or a dirty production function (akin to our vintages), where clean production is linear in labor and dirty production (d) requires an additional fossil input o_{ij}. The production function reads:

$$y_{ij} = \left(l_{ij}\right)^{\alpha} \cdot \left(o_{ij}\right)^{1-\alpha} \quad \Rightarrow \quad o^*_{ij} = \left(\frac{1-\alpha}{\alpha}\frac{w}{p^0}\right) l_{ij},$$

where $\alpha \in (0, 1)$ governs the factor shares in production with the dirty technology and o^*_{ij} denotes the firms' profit-maximizing use of the fossil input. The variable p^0 is the relative price of the dirty input in units of numeraire. An increase in p^0 reflects an increase in the cost of using the dirty input, potentially as the result of an increased emission tax. That raises the relative costs of producing with dirty rather than clean production vintages. Inserting optimal fossil inputs into the production function gives the production function and normalizing

dirty productivity to 1 gives $y_{ij} = a^g l_{ij}$, where the relative productivity of green technology a^g equals

$$a^g = \left(\frac{\alpha}{1-\alpha} \frac{p^0}{w} \right)^{1-\alpha}.$$

3.3. Static Optimization

The firm that offers the lowest quality-adjusted price to consumers faces the demand function

$$y_{ij} = Y p_{ij}^{-1}. \tag{1}$$

The unit-elastic demand function applies as long as, adjusted for quality differences, the firm sets its price at a lower level than its closest competitor. The profit-maximizing action is thus to limit-price the firm that is able to set the closest quality-adjusted price. Because the marginal cost of producing a good depend on whether the producer's production method relies on the new or the old technology, the limit price depends on the technology of both the leading and that of the closest competitor firm. If the production method of both firms relies on the same technology vintage their marginal costs are equal, and the leading firm charges a markup λ_{ij} over marginal costs, where λ_{ij} is the quality gap between the leading and the follower firm. If the leading firm uses a different technology vintage than its closest competitor, marginal costs across the two firms differ, and the limit-price markup reflects that. Respectively denoting the technology vintage of the producer by h and the technology used by its closest competitor by h', the markup μ_{ij} charged by firm i on good j equals

$$\mu_{ij} = \begin{cases} \lambda_{ij} & \text{if } h = h' \\ \lambda_{ij} \cdot a^m & \text{if } h = m,\ h' = o \\ \lambda_{ij} / a^m & \text{if } h = o,\ h' = m. \end{cases} \tag{2}$$

It follows that the average markup on goods produced with the modern technology rises with the relative cost of producing goods using the old technology. When the modern technology differs from the old one in relying less on fossil inputs, this effect could arise from policies such as a carbon tax, which raise the markups of green producers while lowering those of dirty producers.

3.4. Innovation

As in Klette and Kortum (2004), firms may hold the production technologies for multiple intermediate goods. To expand their product portfolios, firms invest in R&D. A successful R&D effort grants the firm a frontier patent that allows it to produce a randomly drawn product j using a production method with quality

$$q_{ij} = q_{i'j} \lambda_{ij}, \tag{3}$$

where i' denotes the firm that previously owned the highest-quality patent for product j. In what follows, we assume that all innovations entail the same quality step, i.e. $\lambda_{ij} = \lambda$.[12]

Firms' R&D investments are directed to the two technological vintages, in the sense that firms decide what fraction of their research to allocate towards the development of production methods based on the modern technology vintage, and what fraction to devote to the old technology vintage. This decision is shaped by three factors. First, the expected cost of obtaining a patent that relies on a given technology vintage decreases with the firm's prior experience using that vintage. In other words, firms that are already the leading producers of several products based on vintage $h \in \{m, o\}$ find it easier to expand the range of products they offer with that same technology. Second, the intrinsic cost of innovating in each direction may differ, even abstracting from firms' prior experience; in the specification below this is captured by vintage-specific base capacities. Third, the expected markups associated with producing under the old and the modern vintage differ (depending on a^m), implying that the value of owning a patent also differs across technologies.

Both entrants and incumbents are assumed to have a base innovation capacity in any vintage, denoted η^h, which allows them to innovate in a type of product they do not necessarily produce yet. Formally, firms choose the Poisson arrival rates of patents with production methods that rely on the modern technology vintage (x_i^m) and the Poisson arrival rate for old vintage patents (x_i^o). We implement this by introducing a portfolio-dependent R&D technology, in which the cost of innovation depends on both the scale and the technological composition of the firm's existing expertise. To achieve innovation rates x_i^m and x_i^o, firm i employs researchers according to

$$rd_i(x_i^m, x_i^o) = \frac{\phi}{\psi} N_i^{1-\frac{\psi}{\kappa}} \left[(x_i^m)^\kappa (N_i^m)^{1-\kappa} + (x_i^o)^\kappa (N_i^o)^{1-\kappa} \right]^{\frac{\psi}{\kappa}}, \tag{4}$$

where $\phi > 0$ is a cost shifter, ψ and κ are scalars such that $\psi > \kappa > 1$, and where $N_i = N_i^m + N_i^o$ is the total innovation-relevant size of the firm, defined as the sum of the firm's stocks of research capability in each technology, $N_i^h = n_i^h + \eta^h$. Each stock consists of the number of goods produced with technology vintage h for which firm i is currently the producer (n_i^h) and the base innovation capacity (η^h).

This portfolio-dependent R&D cost function extends the standard innovation technology in, e.g., Klette and Kortum (2004) along two dimensions: firms choose both how much to innovate and how to allocate innovation across technological vintages. To illustrate its structure, let $X_i = x_i^m + x_i^o$ denote total innovation, $s_i^h = x_i^h / X_i$ the share directed toward vintage h,

[12] We focus on calibrations where $\lambda > \max\{a^m, (a^m)^{-1}\}$, so that a firm that develops a patent to produce a good j is able to become the producer of that product irrespective of the technology vintage of its patent, and of the technology vintage of the patent of the previous producer. See De Ridder (2024) for an example of a framework in which differences in marginal costs across firms can prevent firms with the highest-quality patent of a good from becoming the producer.

and $\omega_i^h = N_i^h/N_i$ the corresponding share of the firm's research capabilities. Equation (4) can then be written as

$$rd_i = \frac{\phi}{\psi} N_i \left(\frac{X_i}{N_i}\right)^{\psi} \left[\sum_{h\in\{m,o\}} \omega_i^h \left(\frac{s_i^h}{\omega_i^h}\right)^{\kappa}\right]^{\frac{\psi}{\kappa}}.$$

The first component is the standard isoelastic cost of expanding innovation relative to the firm's knowledge stock. This builds on the standard assumption in, e.g., Klette and Kortum (2004) and Luttmer (2011), that larger firms are more effective innovators because their existing production activities generate organizational capital that facilitates further innovation. Absent financial constraints, it also ensures that firms of different sizes grow at the same rate—a well-established fact in the firm-dynamics literature known as Gibrat's Law—up to the base capacities η^h, which make small firms grow somewhat faster per product. The expression in brackets is at least one and equals one when innovation shares coincide with capability shares. Holding total innovation fixed, directing research away from the composition of existing expertise therefore requires additional resources. This gives firms an endogenous comparative advantage in the technology vintages they have previously developed:

Assumption 1. $\psi > \kappa > 1$, *so that the cost of achieving a given Poisson arrival rate of patents that rely on technology vintage* h, x^h, *declines in the number of products that a firm already produces using vintage* h.

The two curvature parameters in the R&D cost function then serve a distinct purpose. The parameter ψ determines the cost of expanding total innovation while holding its composition fixed. The parameter κ governs the cost of changing its composition and, as we show below, the responsiveness of relative innovation rates to relative patent values, which has elasticity $1/(\kappa-1)$. For $\psi = \kappa$, the cost function becomes additively separable in both technologies, as in Acemoglu et al. (2016). In the calibrations that we focus on ($\psi > \kappa$), the cross-partial derivative of research costs with respect to the two innovation rates is positive: increasing innovation in either vintage raises the marginal cost of innovation in the other. This represents the idea that research across the two vintages draws on common firm resources. Technological experience thus gives firms a comparative advantage in the vintages in which they have previously successfully innovated, while positive baseline capabilities (η^h) allow them to develop technologies outside their existing product portfolios. Experience therefore shapes the direction of innovation without making specialization irreversible.[13]

3.5. Financial Constraints

Innovation by incumbent firms is subject to a cash-in-advance constraint and is financed by funds provided by competitive creditors. These creditors are willing to lend at the rate r_t, which is the return on household deposits. We assume that if a firm attempts to default on

[13] For empirical evidence on firm-level path dependence see Aghion et al. (2016) and references therein.

its credit obligations, creditors can recover only a fraction θ_i of firm i's revenue py_i for debt repayment. Hence, the creditors' participation constraint is satisfied only when the firm's debt d_i does not exceed the recoverable portion of revenue:

$$d_i \leq \theta_i p y_i. \tag{5}$$

This formulation is consistent with a growing empirical literature documenting that financial constraints typically depend on earnings flows rather than on firms' capital assets (see, e.g., Lian and Ma 2021, Drechsel 2023).[14] The model abstracts from a decline in financial constraints through retained earnings (see, e.g., Moll 2014): profits are paid out in dividends to the household every period.

The fraction of revenue that borrowers can appropriate, θ_i, has both an idiosyncratic and an aggregate component: $\theta_i = \vartheta_i \cdot \Theta_t$, where Θ_t summarizes the aggregate state of financial conditions. The idiosyncratic component, ϑ_i, reflects the number and quality of a firm's relationships with creditors. Through variation in the aggregate financial condition, Θ_t, we introduce a financial shock outside of the balanced growth path. At Poisson rate $\nu^{\uparrow}$, firms form new lending relationships—or, equivalently, existing creditors improve their screening technologies—thereby increasing the share of revenue they can pledge. Conversely, at rate $\nu^{\downarrow}$, firms lose lending relationships, which reduces the amount of revenue they can borrow against. Entrants begin with the weakest credit access, $\vartheta_i = \underline{\vartheta}$. The key assumption is that firms are more likely to face an easing of their financial constraints rather than a worsening of their financial constraints over time:

Assumption 2. *The Poisson rate at which firms face an increase in θ exceeds the rate at which firms face a decrease in θ, that is, $\nu^{\uparrow} > \nu^{\downarrow}$.*

Assumption 2 yields that younger firms, on average, are more financially constrained than older firms. The fraction of revenue that creditors can jointly capture is bounded above by $\overline{\vartheta}$, beyond which ϑ_i cannot further improve.

3.6. Entry, Exit, and Creative Destruction

Firms endogenously enter and exit the economy. There is a continuum of potential entrants that employ rd^e researchers to develop patents that rely on the base innovation capacity following the same specification as for incumbents:

$$rd_e(e^m, e^o) = \frac{\phi_e}{\psi} N_e^{1-\frac{\psi}{\kappa}} \left[(e^m)^{\kappa} (\eta^m)^{1-\kappa} + (e^o)^{\kappa} (\eta^o)^{1-\kappa} \right]^{\frac{\psi}{\kappa}},$$

[14] Lian and Ma (2021) show that collateral requirements in debt contracts commonly take the form of covenants restricting ratios of debt or interest payments to accounting profits. Equation (5) models borrowing constraints as a function of revenue rather than profits because accounting profits (e.g., EBITDA) include factor payments for capital and therefore do not correspond to the economic rents in our framework. This is also how covenants are modeled in Ottonello and Winberry (2024).

where e^m denotes the entry rate of firms that initially operate using the clean technology and e^o is the rate at which firms operating an old-technology product line enter. Note that the size of entrants depends entirely on base innovation capacities, hence $N_e = \eta^m + \eta^o$. As with incumbent innovation, entrants become the owner of the highest-quality patent of a random product which is a γ multiple of the level of quality of the previous producer. Without loss of generality, we assume that entrants' innovations are of the type – modern or old – in which the innovation was directed.[15]

Firms exit the economy when they cease to be the producer of any of the economy's goods. A firm will stop producing one of its products if an innovator, be it an entrant or an incumbent, develops a higher-quality version of one of the goods that it produces. A multi-product firm that is hit by creative destruction stops producing one of its products. Single-product firms that see their sole product creatively destroyed exit. This happens at the rate of creative destruction, τ:

$$\tau = \int_0^1 \left(x_i^c + x_i^d \right) di + e^c + e^d. \tag{6}$$

As each creatively destroyed product's quality improves by a multiple λ, aggregate productivity growth in the economy is given by

$$g = \tau \ln \lambda. \tag{7}$$

3.7. Dynamic Optimization

Let $V_t(J, \theta)$ denote the value function of a firm with financial state θ and patent portfolio J, which is a multiset detailing both the technology vintage with which the firm produces, and the technology with which its second closest competitor produces. The Bellman equation reads as follows:

$$rV(J,\theta) - \dot{V}(J,\theta) = \max_{\substack{x^m, x^o \\ d \leq \theta p y}} \left\{ \begin{array}{c} \sum_{j \in J} \pi^{h_j h'_j} Y \\ +\nu^{\uparrow} \left[V_t(J, \theta^{\uparrow}) - V_t(J,\theta) \right] + \nu^{\downarrow} \left[V_t(J, \theta^{\downarrow}) - V_t(J,\theta) \right] \\ +\tau n^m \, \mathbb{E}\left[V_t(J \setminus \{m, h'\}, \theta) - V_t(J,\theta) \right] \\ +\tau n^o \, \mathbb{E}\left[V_t(J \setminus \{o, h'\}, \theta) - V_t(J,\theta) \right] \\ +x^m \, \mathbb{E}\left[V_t(J \cup \{m, h'\}) - V_t(J,\theta) \right] \\ +x^o \, \mathbb{E}\left[V_t(J \cup \{o, h'\}) - V_t(J,\theta) \right] \\ -w \cdot rd(x^m, x^o) - F(J,\theta) \end{array} \right\} \tag{8}$$

[15] We abstract from mergers and acquisitions (M&A), through which constrained young firms could sell their green innovations to unconstrained mature firms. Models with M&A typically assume a search and matching friction between buyers and sellers (e.g. Akcigit et al., 2016; David, 2021; Fons-Rosen et al., 2026). Our model therefore implicitly assumes that this friction is strong. This is not unreasonable: Fons-Rosen et al. (2026) report that only about 4% of innovative startups are acquired within six years of their creation. For our empirical application in Section 4.1, Biermann and Huber (2024) provide direct evidence that exposed firms are not more likely to exit.

The first row captures the firm's instantaneous flow profit, given by the sum of product-level operating profits $\pi^{h_j h'_j} Y$ across all patents $j \in J$, where $\pi^{h_j h'_j} = (\mu^{h_j h'_j} - 1)/\mu^{h_j h'_j}$ and where, in turn, markups are given by (2) for $\lambda_{ij} = \lambda$. The second row describes the expected change in firm value due to an improvement in its financial maturity: with Poisson rate $\nu^{\uparrow}$, the firm transitions from θ to a more favorable financial state $\theta^{\uparrow}$, generating a corresponding jump in value $V_t(J, \theta^{\uparrow}) - V_t(J, \theta)$. The third row mirrors this for deterioration in financial maturity: with probability flow $\nu^{\downarrow}$, the firm moves to a tighter constraint $\theta^{\downarrow}$, reducing its continuation value by $V_t(J, \theta^{\downarrow}) - V_t(J, \theta)$. The next two rows represent creative destruction acting on the firm's patent portfolio: existing modern-vintage products are displaced by outside innovators at rate τn^m, and old-vintage products at rate τn^o, with the loss of a patent reducing firm value from $V_t(J, \theta)$ to the value of the portfolio with that patent removed. The following two rows capture the firm's own R&D investments: by choosing innovation intensities x^m and x^o, the firm can acquire new modern- and old-vintage patents, each increasing expected firm value by the jump from $V_t(J, \theta)$ to the value with the new patent added. The first term in the last row subtracts R&D costs, which depend on the number of product lines n^m and n^o and the convex cost function $w_t \cdot rd_{it}(x^m_{it}, x^o_{it})$. Finally, we follow Akcigit and Kerr (2018b) and assume that firms face a fixed operating cost $F(J, \theta)$ that subsumes changes in the option value of R&D that arise as a result of changes in firm size and technological composition. This keeps the solution to the model analytically tractable.[16]

Proposition 1. *The value V_t of a firm grows at a constant rate g over the balanced growth path*

$$\dot{V}(J, \theta) = g V(J, \theta)$$

and can be expressed as the product of aggregate income Y and a time-invariant function of the number of modern and old-vintage products that the firm produces:

$$V_t(J, \theta) = (n^m V^m + n^o V^o) Y, \tag{9}$$

where V^m and V^o respectively denote the present value of expect profits from producing a modern or old vintage product. The first-order condition for the arrival rate of ideas in technology vintage $h \in \{m, o\}$ is given by

$$x^h(J, \theta) = \left(\frac{Y}{w} \frac{1}{\phi N^{1-\frac{\psi}{\kappa}} S(J)^{\frac{\psi}{\kappa}-1} (1 + \mathcal{M}(J, \theta))} \right)^{\frac{1}{\psi-1}} \left(V^h\right)^{\frac{1}{\kappa-1}} N^h \tag{10}$$

where $\mathcal{M}(J, \theta) \geq 0$ is the shadow price of financing R&D expenditures, which declines in a firm's financial maturity θ, and $S(J) = (V^m)^{\frac{\kappa}{\kappa-1}} N^m + (V^o)^{\frac{\kappa}{\kappa-1}} N^o$. This closed form makes explicit that the financing wedge $1 + \mathcal{M}$ scales the overall level *of innovation (with elasticity $\frac{1}{1-\psi}$) while*

[16] In absence of this simplification, the optimal R&D in either technology is quantitatively similar, but there exists no closed form solution for the value of owning a product, complicating the analytical analysis.

cancelling from its direction*, since* $x^m/x^o = (N^m/N^o)\,(V^m/V^o)^{\frac{1}{\kappa-1}}$*. The optimal entry rate is given by*

$$e^h = \left(\frac{Y}{w}\,\frac{1}{\phi_e\, N_e^{1-\frac{\psi}{\kappa}}\, S_e^{\frac{\psi}{\kappa}-1}\,(1+\mathcal{M}^e)}\right)^{\frac{1}{\psi-1}} \left(V^h\right)^{\frac{1}{\kappa-1}} \eta^h \tag{11}$$

where $\mathcal{M}^e$ *is the financing shadow price for entrants,* $N_e = \eta^m + \eta^o$*, and* $S_e \equiv (V^m)^{\frac{\kappa}{\kappa-1}}\eta^m + (V^o)^{\frac{\kappa}{\kappa-1}}\eta^o$*. Entrants thus face the same nested isoelastic technology as incumbents as in equation (4) evaluated at zero product experience. They also face the same financing constraint as incumbents, with the shadow price* $\mathcal{M}^e$ *determined by the same revenue-based budget as in equation (5) evaluated at an entrant's anticipated financial maturity—the lowest level,* $\underline{\vartheta}$*—and anticipated size of a single product line. Entry is therefore treated symmetrically to the youngest incumbents.*

Proof. See Appendix A.2.

The proposition shows that a firms' innovation rates increase in the value of becoming a good's producer, which is the sum of the discounted value of the good's expected flow of profits. The optimal innovation rates decline in the cost of R&D, which is a combination of the cost of hiring researchers and the shadow cost of obtaining the necessary financing.

3.8. Stationary Distributions of Maturity, Size, and Technology-Type

The joint distribution of three firm-level state variables are relevant for the equilibrium: the distribution of financial maturity θ, its joint distribution with the number of modern and old vintage products that a firm produces, and the fraction of products that is produced with the old and the new technology vintage. A firm is characterized by three state variables: the number of modern product lines (n^m), the number of old product lines (n^o), and financial maturity (θ). Firms can move across these states because their financial conditions improve or deteriorate, they gain products through innovation, and they lose products through creative destruction. Firms that lose their last product exit; entry replenishes mass at the lowest financial-maturity level, with entrants starting either as modern or old producers.

Given innovation and entry rates, these forces define a Markov process over the full state space. The stationary distribution is the invariant distribution of that process: it is the unique cross-section that is reproduced by the model's own transition dynamics. A convenient way to write this is to separate incumbent transitions from entrant inflows. Let M be the vector of masses over active firm states, let T be the matrix with transition rates implied by innovation, destruction, financial-state movements, and let E be the vector of entry inflows. The law of motion is $\dot{M} = TM + E$. In a stationary equilibrium, $\dot{M} = 0$, so that

$$M = -T^{-1}E.$$

That is, the stationary cross section is just the one that exactly balances within-state reallocation and entry inflows. Details on computation are provided in Appendix C.

Defining the stationary mass of firms of a combination of firm states by $M_{n^m,n^o}(\theta)$, we can then calculate key moments such as the stationary equilibrium fraction of products that is produced with the modern technology vintage:

$$F = \frac{\sum_\theta \sum_{n^m,n^o} n^m M_{n^m,n^o}(\theta)}{\sum_\theta \sum_{n^m,n^o} (n^m + n^o) M_{n^m,n^o}(\theta)}. \tag{12}$$

3.9. Aggregate Variables

We next characterize the economy's aggregate variables. The equilibrium wage is given by

$$w = \exp\left(\int_0^1 \ln q_j dj\right)(a^m)^F \left(\exp\left(\overline{\ln \mu^m}\right)^F \exp\left(\overline{\ln \mu^o}\right)^{(1-F)}\right)^{-1}, \tag{13}$$

where the first two terms together form the standard CES productivity index based on the quality at which goods are produced, while the variables in the third term are

$$\overline{\ln \mu^m} = F \ln \lambda + (1-F)\ln(\lambda/a^m) \quad \text{and} \quad \overline{\ln \mu^d} = F \ln\ln(\lambda \cdot a^m) + (1-F)\ln\lambda.$$

The third term in (13) captures the degree to which wages are suppressed by the fact that firms have market power and thus charge markups, and the fact labor is combined with other inputs in the production of dirty products.

Turning to aggregate output, the economy's GDP is determined by productivity and the fraction of labor employed to produce goods (L^p):

$$Y = L^p \exp\left(\int_0^1 \ln q_j dj\right)(a^m)^F \mathcal{W}. \tag{14}$$

Derivations are provided in Appendix A. The term $\mathcal{W}$ captures the productivity loss that arises when firms have heterogeneous markups, because products that sell at a high markup are demanded in inefficiently low quantities. A term similar to the latter is derived in Peters (2020). Production labor is determined by clearance of the labor market. Households supply their single unit of labor inelastically, so that

$$1 = L^m + L^o + L^{rd} + L^e, \tag{15}$$

where L^c and L^d is the labor used to produce clean and dirty intermediate goods while L^{rd} and L^e denote the labor required for innovation by incumbents and entrants. Incumbent R&D labor is given by

$$L^{rd} = \frac{\phi}{\psi} \sum_\theta \sum_{n_m,n_o} M_{n_m,n_o}(\theta) N^{1-\frac{\psi}{\kappa}} \left[x_m(n_m,n_o,\theta)^\kappa (N^m)^{1-\kappa} + x_o(n_m,n_o,\theta)^\kappa (N^o)^{1-\kappa}\right]^{\frac{\psi}{\kappa}}, \tag{16}$$

and entrant R&D labor is

$$L^e = \frac{\phi_e}{\psi} N_e^{1-\frac{\psi}{\kappa}} \left[(e^m)^\kappa (\eta^m)^{1-\kappa} + (e^o)^\kappa (\eta^o)^{1-\kappa} \right]^{\frac{\psi}{\kappa}} = r d_e(e^m, e^o). \tag{17}$$

3.10. Equilibrium

The following definition characterizes the equilibrium:

Definition 1. *The economy is in a balanced growth path equilibrium if for every t and for every firm maturity level k, the variables e^m, e^o, τ, r, L^p, $\mathcal{W}$ and the functions $x^m(J,\theta)$, $x^o(J,\theta)$, V^m, and V^o are constant while Y and w grow at the constant rate g that satisfies (7) with creative destruction rate (6). The value of owning a firm is given by (9), while innovation rates for incumbents and entrants are respectively given by (10) and (11). The equilibrium fraction of modern products F is given by (12). The interest rate obeys the Euler equation, output and wage are respectively given by (13) and (14). Appendix A provides expressions for L^p, using labor market clearance (15) and markup dispersion $\mathcal{W}$.*

3.11. Financial Tightening During a Technological Transition

We next explain why a tightening of financial conditions can disproportionately affect innovation in the modern technology vintage when the economy is in transition. We define such a transition as a phase during which the fraction of goods produced with the modern vintage, F, is rising. Letting X^h denote the combined flow of incumbent and entrant innovation directed toward vintage h, this occurs whenever modern innovation exceeds the flow of modern products displaced through creative destruction:

$$\dot{F} = X^m - \tau F > 0, \qquad \tau = X^m + X^o.$$

A technological transition begins after an increase in the relative profitability of producing with the modern vintage. In the model, an increase in a^m raises the markups of modern producers competing against old-vintage firms and lowers those of old-vintage producers competing against modern firms. This raises the relative value of developing modern production methods and shifts innovation toward that vintage. As these innovations replace existing products, the fraction of goods produced with the modern technology increases.

Early in the transition, path dependence gives young firms a comparative advantage in modern innovation. To see this, the innovation rules in equations (10) and (11) imply

$$\frac{x_i^m}{x_i^o} = \frac{n_i^m + \eta^m}{n_i^o + \eta^o} \left(\frac{V^m}{V^o} \right)^{1/(\kappa-1)}, \qquad \frac{e^m}{e^o} = \frac{\eta^m}{\eta^o} \left(\frac{V^m}{V^o} \right)^{1/(\kappa-1)}.$$

The relative profitability of modern innovation affects entrants and incumbents through the same product values. Their allocation of research nevertheless differs because incumbents

have accumulated technological experience. Consider, for example, an incumbent that produces only old-vintage goods. Its ratio of modern to old innovation is lower than that of an entrant by a factor $\eta^o/(n_i^o + \eta^o) < 1$. The incumbent can develop modern production methods, but its existing expertise makes further old-vintage innovation relatively less costly. New firms have no such inherited advantage in the old technology. Firms that enter and expand using the modern vintage then accumulate expertise in that direction, giving young cohorts an important role in its diffusion.

This matters because financial maturity develops gradually. Entrants begin with the weakest credit access, so that younger firms are more financially constrained on average. A tightening of aggregate financial conditions (i.e., a fall in Θ_t) therefore disproportionately reduces innovation by these firms. The financing wedge that such a tightening induces scales both innovation rates within a firm by the same factor, leaving their ratio unchanged. Its effect on the aggregate direction of innovation depends on which firms undertake modern and old-vintage research.[17]

We can express this composition effect formally. Hold fixed wages, revenues, product values, and the distribution of firms over product portfolios and idiosyncratic financial maturity. Let b^h denote the share of innovation in vintage h undertaken by innovators whose financing constraint binds, including entrants. Since R&D costs are homogeneous of degree ψ, both innovation rates of a constrained firm have elasticity $1/\psi$ with respect to Θ, while those of an unconstrained firm are locally unaffected. For a marginal change that leaves the set of binding constraints unchanged, aggregation therefore gives

$$\frac{\partial \log(X^m/X^o)}{\partial \log \Theta} = \frac{b^m - b^o}{\psi}.$$

Thus, whenever modern innovation is more concentrated among financially constrained firms, a tightening reduces modern innovation proportionately more than old-vintage innovation. The asymmetry comes from the interaction between technological experience and financial maturity: path dependence directs young firms toward the emerging technology, while their limited credit access makes their innovation more sensitive to financial conditions.

The effect of financial tightening consequently depends on the stage of the transition. Firms that develop expertise in the modern vintage early in the transition may still have weak lending relationships when a crisis arrives. If the crisis arrives later, these firms have had more time to mature financially. Section 4 examines these mechanisms in the micro data and quantifies their implications for the transition. The quantitative analysis allows wages, product values, and the distribution of firms to adjust, and establishes how the resulting effect on modern innovation varies with the timing of the financial shock.

[17] In the quantitative experiment on the effect of a financial crisis on green innovation in Section 4, we therefore target the fraction of green innovation that comes from young firms prior to the crisis.

4. Application: Green Innovation After the Global Financial Crisis

In this section, we use the framework in Section 3 to quantify how much the self-selection of young firms into green innovation can explain the slowdown in green innovation after the Global Financial Crisis. Our goal is twofold. First, we use micro data to scrutinize the empirical validity of the model's mechanisms (Section 4.1). Second, we use the micro data to discipline the model's parameters (Section 4.2) and then study the path of green innovation after a financial shock of the size experienced after the Global Financial Crisis (Section 4.3).

4.1. Micro Evidence

We use micro data on the heterogeneous exposure of German firms to the Global Financial Crisis to study its effect on green patenting in subsequent years and thereby validate the model's predictions. Green technologies are a natural example of the model's "modern" technology, as their share in total patenting had risen steadily over the two decades before the crisis (recall Figure 1). German firms are particularly well suited for this analysis because, relative to their American counterparts, they rely more heavily on bank credit than on market finance (Huber 2018). As we explain below, this creates plausibly exogenous variation in firms' exposure to the crisis through the identity of their bank relationships, allowing us to isolate the effect of tighter credit while controlling for confounding macroeconomic factors.

The model delivers three predictions for green innovation during the crisis. First, it predicts that young firms are responsible for a disproportionate share of total green innovation. That is, the fraction of green patents that can be attributed to young firms exceeds that fraction for non-green patents prior to the crisis. Second, the average negative average effect of exposure to the crisis on green panting should exceed the effect on non-green patenting. Third, it predicts that young firms cut their overall patenting while mature firms (whose financial constrains may not bind) do not, so that the larger effect of exposure to tight credit on green patenting is driven by the age composition of green innovators.

Strategy To test these predictions, we combine firm-level measures of green versus non-green innovation based on IPC patent classification codes with data on whether firms relied on loans from to Commerzbank prior to the Global Financial Crisis. We use the fact that firms that relied on Commerzbank were disproportionately subject to a tightening of their credit constraint, as shown in Huber (2018).[18] This enables us to assess the effect of tight credit on (green) innovation while holding constant other macroeconomic variables that might affect firms' investments in (green) innovation, such as energy prices, fiscal policy including subsidies for emissions-reducing technology, or changes in investor preferences.

[18] Huber (2018) looks at the effects of Commerzbank exposure on employment, investments and overall patenting. Its Online Appendix B provides a detailed analysis of the trading losses incurred by Commerzbank and the effect this had on lending. Huber also provides extensive balance checks to show that firms that rely on Commerzbank loans have similar pre-crisis characteristics to other firms.

Commerzbank was a large German bank prior to the crisis, with a market share of around 9% in 2006. It incurred significant trading losses on the U.S. subprime market in 2008, causing the bank's equity to fall by 68%. These losses forced Commerzbank to cut its assets significantly. As Basel II regulation assigns a significant risk weight to corporate loans, reduced credit supply to corporations are an effective way of doing so. This led Commerzbank to reduce its lending stock by 35% between 2006 and 2013, which is around three times the average cut in lending stock by German banks after the Global Financial Crisis. Given the long-term nature of relationships between firms and banks, induced by the fact that repeated interaction improves the ability of banks to screen and monitor lenders (e.g., Boot 2000), this means that firms that relied on credit from Commerzbank prior to the Global Financial Crisis faced a greater tightening of their credit constraint.

The empirical strategy proceeds in three steps. First, we assess the relationship between firm age and patenting in green technologies for German firms in the years prior to the Global Financial Crisis. Second, we perform a difference-in difference estimation to assess the extent to which the flow of green and non-green patenting react differently to the Global Financial crisis in firms with high versus low pre-crisis dependence upon Commerzbank lending. Third, we perform the triple-difference-in-difference regression, where we assess whether the effect of exposure to Commerzbank on patenting is heterogeneous with respect to firm age. To implement the latter two, we estimate the parameters of the following equation using Santos Silva and Tenreyro (2006)'s Pseudo-Poisson Maximum Likelihood estimator:

$$E_t[y_{it} \mid X_{it}, i, t] = \exp\left(\sum_{\tau \neq \tau_0} \gamma_t \mathbb{I}_{t=\tau} \text{Commerzbank Exposure}_i + \beta_t' \tilde{X}_{it} + \phi_i + \psi_t\right), \tag{18}$$

for the difference-in-difference, where y_{it} denotes firm i's flows of green and dirty patents in year t, and $\mathbb{I}_{t=\tau}$ is the indicator function so that γ captures the time-varying effect of pre-crisis dependence on loans from Commerzbank on the flow of patents. That is, we expect the coefficients γ_t to be negative in the aftermath of Commerzbank's 2008-2012 reduction in credit supply. Time effects ψ_t control for macroeconomic events common to all firms during the global financial crisis, such as changes in energy prices, fiscal incentives for green innovation, or overall changes in investor preferences. For the triple-difference-in-difference, the estimation equation is

$$E_t[y_{it} \mid X_i, i, t] = \exp\left(\sum_{\tau \neq \tau_0} \gamma_t \mathbb{I}_{t=\tau} \text{Commerzbank Exposure}_i \times D_i^{Age} + \beta_t' \tilde{X}_{it} + \phi_i + \psi_t\right), \tag{19}$$

where D_i^{Age} is a dummy that equals 1 for firms that are below the median age of firms in the sample and zero otherwise. We saturate this estimation equation, i.e., we include interaction terms between time and both firm age and Commerzbank exposure as part of the set of controls $\tilde{X}_{it}$.

Data To implement the empirical strategy, we combine firm-level data on exposure to Commerzbank with firm-level accounting data and data on patenting.

We measure exposure to Commerzbank from the fraction of a firm's pre-crisis relationship banks that is a branch of Commerzbank. Relationship banks (*Hausbanken*) are the primary banks that firms obtain banking services from, and are based on firms' response to surveys from credit rating agency Creditreform in 2006. Following Huber (2018), we construct a measure of reliance on Commerzbank that equals the portion of a firms' set 2006 relationship banks H_i that is a Commerzbank branch:

$$\text{Commerzbank Exposure}_i = \sum_{h \in H_{i,2006}} \frac{\mathbb{I}_{h=\text{Commerzbank Branch}}}{\mid H_{i,2006} \mid},$$

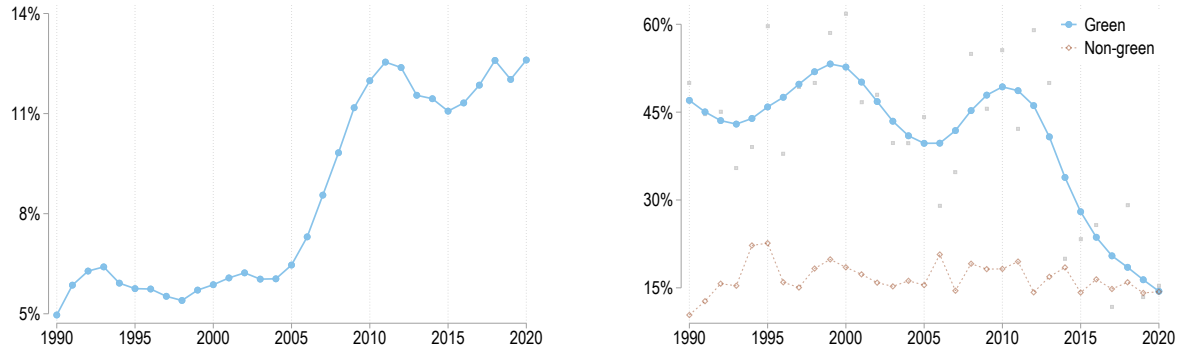
where the indicator function equals one if bank h is a Commerzbank branch. The index is naturally bounded between 0 and 1 and equals 0.17 on average, with a 90th percentile of 0.5. This means that few firms rely solely on Commerzbank as their relationship bank.

The accounting data come from Dafne, the German subset of Bureau van Dijk's (BVD) Historical Orbis database, and include firms' balance sheet and income statement information. Patent data is from PATSTAT, which provides worldwide coverage of patents from more than 90 patent offices. We count patent families so an innovation is not double counted if filed in multiple jurisdictions. We merge the two datasets using BVD identifiers, company names and other information. We restrict the sample to firms that have filed at least one patent since 1990. As in Huber (2018) we condition on some non-missing data on employment, wages, loans, value added and fixed assets between 2007 and 2012. The resulting sample contains 601 firms observed for up to 18 years. The panel does not condition on survivors: some firms exit and have no patenting. Appendix Table B1 reports some summary statistics.

We measure green innovation by assigning patents to green and non-green technologies using the OECD classification proposed by Haščič and Migotto (2015). They identify green technologies based on International Patent Classification (IPC) codes. The classification includes four broad groups: environmental management, water-related adaptation, biodiversity protection, and climate change mitigation, which accounts for the largest share of green IPC codes. We classify a patent as green whenever at least one of its IPC codes falls in the OECD definition. A firm's annual patent count is then defined as the number of green and non-green patent applications it files in a given calendar year.

Results Before turning to the model's predictions, we first verify that Germany experienced a slowdown in the rise of green patents as a share of total patenting. Figure 6a shows that green patents accounted for 4.9% of all German patents in 1990. This share rose only modestly over the following decade, before accelerating rapidly from 2005 onward, increasing from 6.5% to a peak of 12.5%. Consistent with the global patterns documented in Figure 1 of the Introduction, that rise stalled in Germany after 2011. Between 2011 and 2020—the last year

Figure 6. Green Patenting Trends During Global Financial Crisis in Germany



(a) Green Patents (% of Total Patents)

(b) Younger Firms (% of Total Patents)

Notes: The left-hand figure plots the fraction of German patent applications (out of total applications) that relates to green technologies. This figure is based on the universe of firms in PATSTAT. The right-hand figure plots the percentage of patents that comes from below-median aged firms separately for green patents (blue-circled lines) and for non-green patents (brown-squared lines). This figure is based on the matched PATSTAT-Dafne-Creditreform dataset. Lines plot 5-period moving averages—the underlying raw data is plotted with grey scatters for green patents.

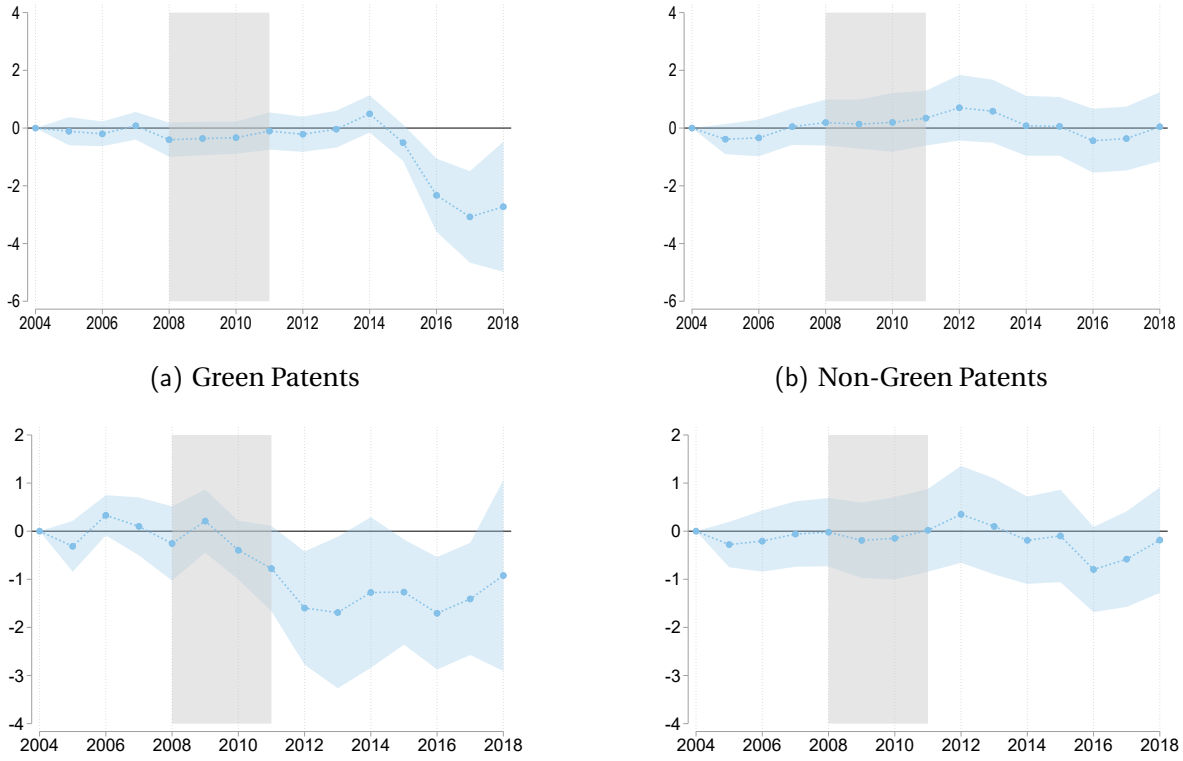
we plot because of patent grant delays—green patent applications accounted for between 11% and 12.6% of total patents.

Turning to the first prediction of the model, Figure 6b confirms that younger firms played an outsized role in green patenting in the years prior to the crisis. Because we need to observe firm age to analyze the contribution of young firms, we perform this analysis on the subset of patents that is part of the merged PATSTAT-Dafne-Creditreform dataset. The blue-circled line plots a moving average of the fraction of all green patents that are linked to firms with below-median age, while the grey scatters plot the underlying data. Between 1990 and 2010, young firms are responsible for around 45% of green patents, with peak contributions of over 61%. In contrast, the contribution of young firms to patenting in non-green technologies is more modest, averaging only 16.7% per year. Thus, younger firms appear to be sorting in green innovation, as predicted by our framework.

Considering the drivers of the slowdown of green patenting, Figure 7 provides the results of the difference-in-difference estimation of equation (18). It lends evidence in support of the model's prediction that green innovation declines because it is more sensitive to a tightening of financial conditions. The left-hand figure plots the effect of greater exposure to the Global Financial Crisis through Commerzbank on green patents and the right-hand figure does the same for non-green patents. The grey shaded area covers the period 2008 to 2011, which is when firms that relied on loans from Commerzbank were actively subject to tighter credit than other firms.[19] Confidence bounds are at the 95% level using standard errors clustered at the firm level. The figure shows that exposure to the crisis has no meaningful effect on innovating in non-green technologies, whereas it had a significantly negative effect on green

[19] Biermann and Huber (2024) note that debt of firms with exposure to Commerzbank remained depressed after that, and had not rebounded by the end of their sample in 2015.

Figure 7. Effect of Commerzbank Exposure on Patent Applications



(a) Green Patents

(b) Non-Green Patents

(c) Green Patents - Additional Controls

(d) Non-Green Patents - Additional Controls

Notes: The figure plots the effect of exposure to Commerzbank on green patents (left) and non-green patents (right). Patents are green if at least one IPC code relates to environmental management, water-related adaptation technologies, biodiversity and ecosystem health, or climate-change mitigation (OECD classification; Haščič and Migotto 2015). Confidence bounds are at the 95% level based on standard errors clustered at the firm level. Additional controls include controls for patent stocks and three-digit industry year effects.

innovation. The point estimates are large: the elasticity of green patenting with respect to Commerzbank dependence is about 3 by 2018. Note, however, that few firms rely solely on loans for Commerzbank – the average value of the exposure variable is 0.17 with a 90th percentile of 0.5. A firm with an average (90th percentile) dependence on Commerzbank will therefore have 28% (45%) fewer green patents than a firm that has no direct exposure.

Turning to the third test of the mechanism, we assess whether firm age drives the negative effect of Commerzbank exposure on green patenting in Figure 7. To do so, we estimate the triple-difference specification in equation (19). The results are reported in Table 1. From left to right, the columns show the effect of Commerzbank exposure for the full sample, for firms below the median age, and for firms above the median age. The table shows that young firms reduce both green and non-green innovation, with coefficients of -0.886 and -0.664, respectively. By contrast, mature firms do not reduce innovation in either category.[20] This is precisely what the model predicts: the overall negative effect of Commerzbank exposure on

[20] In the next section, we show that in our model there may even be a positive impact on innovation of older firms due to less creative destruction emanating from younger firms. This is consistent with the positive coefficients in the last two columns of Table 1.

Table 1: Effect of Commerzbank Exposure on Green and Non-Green Patenting by Age

	Average Effect		Age Below Median		Age Above Median	
	Green	Non-Green	Green	Non-Green	Green	Non-Green
Commerzbank Exposure	-0.506***	-0.107	-0.886***	-0.664*	0.950*	0.303
(Effect by Age)	(0.166)	(0.334)	(0.321)	(0.350)	(0.555)	(0.474)

Notes: PPML regressions of patent counts. The coefficient measures the effect of Commerzbank Exposure interacted with a dummy that equals 1 after 2012. Middle and right columns additionally interact with age dummy D_i^{age}. Firm-clustered standard errors are in parentheses. *, **, *** measure significance at the 10, 5, 1% level, respectively. All columns include firm and year fixed effects. Green innovation regressions are based on 2,700 observations, non-green innovation regressions are based on 7,080 observations.

green innovation is driven by the combination of: (1) younger firms cutting *all* innovation in response to tight financial conditions, and (2) younger firms specializing in green innovation.

4.2. Model Quantification

We next use this micro evidence to quantify the model. Our goal is to measure how much the endogenous self-selection of younger firms into new technologies contributes to the differential effect of tighter financial conditions on new versus old technologies. Specifically, we ask whether a uniform tightening of aggregate financial conditions in the model can account for a substantial share of the slowdown of green patenting relative to overall patenting around the Global Financial Crisis in Germany.

Approach Our quantification strategy proceeds in two steps. First, we structurally estimate the model to match a combination of pre-1998 moments from the German micro data and the German economy more broadly, as well as the pre-Global Financial Crisis rise in green patenting by young firms documented in Figure 6, the age gradient of the response to Commerzbank exposure in Table 1, and the age profile of credit rejection among German firms. The pre-1998 moments pin down the initial steady state, while the remaining moments discipline the transition from non-green to green innovation in the counterfactual scenario without a financial crisis, as well as the financial parameters. Second, in the main experiment, we subject the model to a tightening of credit supply equal in magnitude to that experienced in Germany after 2007.

Innovation and General Parameters We discipline the model's innovation parameters, as well as the discount rate ρ, using either external calibration or structural estimation (see Table 2). We set the discount rate ρ to 0.02, a standard value in the literature (e.g. Akcigit and Kerr (2018b), Acemoglu et al. 2018, Aghion et al. 2023).

We set the overall curvature of R&D costs, ψ, to 2. This parameter can be linked to the elasticity of R&D with respect to user costs, ϵ, using that $\psi = (1-\epsilon)/\epsilon$. A large literature estimates this elasticity using firm-level responses to R&D tax credits. For example, Appelt et al. (2022) study micro evidence across OECD countries and find elasticities around -0.6, which would imply $\psi = 2.67$. More broadly, Bloom et al. (2002) discuss values of the elasticity

between -0.5 and -1.0, implying ψ between 2 and 3. We set $\psi = 2$, consistent with Acemoglu et al. (2018), Akcigit and Kerr (2018b), and De Ridder (2024).

The R&D production function also contains two novel parameters. The first new parameter, κ, governs the *within-firm* allocation of research across green and non-green research and development: when $\kappa \to \psi$, costs become approximately separable across modern and old-vintage R&D, whereas lower values of κ generate stronger cross-effects and make firms' R&D allocation more sensitive to relative values and experience. This means that κ disciplines the extent of technological specialization: lower κ makes firms concentrate research more sharply in the vintage in which they have a comparative advantage. The second parameter, η^h, determines the baseline R&D capacity that a firm has in research direction h if it has never patented in the technology. We impose symmetry in this base capacity, so that $\eta^h = \eta$.

To discipline these parameters we use the German patent data over 1985–1995, before the transition begins. We approximate the number of active green and non-green products that a firm has by its previous patenting in either technology, adjusted for the expected number of patents lost due to creative destruction.[21] We use the fact that the first-order condition in Proposition 1 yields that, for a firm with no prior green experience and d non-green products:

$$\frac{x_i^m}{x_i^o} = \frac{\eta}{d+\eta}\left(\frac{V^m}{V^o}\right)^{1/(\kappa-1)}.$$

We estimate a binomial logistic regression for the number of green patents out of total patents in firm-years with positive patenting and no beginning-of-year green stock:

$$G_{it} \mid P_{it} \sim \text{Binomial}(P_{it}, p_{it}), \qquad \log\frac{p_{it}}{1-p_{it}} = \alpha + \beta \mathbf{1}\{d_{it} = 1\},$$

restricting the estimation sample to $d_{it} \in \{0, 1\}$. The intercept measures the log ratio of green to non-green patenting for firms with no prior patent stock. Hence, it pins down κ given the value of patents in the two technologies:

$$\alpha = \frac{\log(V^m/V^o)}{\kappa - 1}.$$

Because V^m/V^o is itself an equilibrium outcome, we impose this restriction jointly with the other steady-state targets described below. The coefficient β on the effect of having one non-green product line identifies the strength of path dependence, $\beta = -\log(1 + 1/\eta)$. We estimate $\hat{\alpha} = -1.80$ and $\hat{\beta} = -0.64$. The latter implies $\eta = 1/(\exp(0.64) - 1) = 1.12$. These estimates imply that having one prior non-green patent reduces the odds that a firm patents in green technology by about $1 - \exp(-0.64) = 47$ percent. The intercept, on the other hand, implies that 14.2 percent of patents by first-time patentees are green. Combined with the patent values in the estimated steady state, we find a value for κ of 1.03.

[21] As we explain below, we externally calibrate the innovation step size. This means that the creative destruction rate can be calculated using the targeted growth rate using the identity in equation (7).

The innovation step λ determines average markups, and thus the profit share in the economy's GDP. We set λ to 1.1 to achieve a profit share of around 9%, consistent with estimates in Barkai (2020).

The remaining innovation parameters are not directly identified from the data and are therefore estimated as part of a larger indirect inference exercise that includes the calibration of the green/dirty profitability and of κ. The first is ϕ, the cost shifter governing research and development (R&D). We pin down this parameter by targeting average German TFP growth of 1.5% between 1985 and 1995. We identify the corresponding parameter for entrant R&D, ϕ^e, by targeting the average rate of entry in Germany over 1985-1995, which was 11.4%.[22]

Green vs. Non-Green Production Cost Parameters We next turn to the relative cost of producing with the green technology, the counterpart in the application to the relative productivity of producing with a new vintage in the model, a^m. Two values must be calibrated. First, we set the initial value of a^m so that the model matches the share of patents that is green in the German micro data between 1985 and 1995, which is 10.6%. Second, because an increase in a^m triggers the transition toward green innovation, we also need to discipline its value in the final steady state. Motivated by canonical endogenous growth models with clean and dirty production—especially Acemoglu et al. (2016)—in which the share of products produced with the non-green technology is proportional to emissions, we set the terminal value of a^m so that the share of products produced with the polluting technology falls by 65% relative to the initial steady state. This corresponds to the decline in emissions required by 2035, relative to 2010, to meet the climate target of limiting global warming to 1.5 degrees Celsius (IPCC 2023).

In addition, we must discipline the path of a^m between the initial and final steady states. We allow a^m to follow a simple sigmoidal transition path and pin down its duration T, the number of years until 99% of the change in a^m has taken place, by targeting the increase in green patenting between the start of the transition and the Global Financial Crisis. Taking the late-1997 Kyoto Protocol agreement as the start of the transition, we target a 2.2-fold increase in the share of green patenting in total patenting, in line with Figure 6. Although the financial crisis may itself have affected the path of non-green production costs—for example through lower oil prices or reduced European green subsidies following austerity, see Hofman and Huisman (2012)—we do not allow the crisis to alter the path of a^m. This is because our objective is to assess whether the self-selection of young firms into green innovation can account for the slowdown in green patenting relative to overall patenting, holding other forces constant.

Steady State Financial Parameters There are four financial parameters to be calibrated. We choose parameter values to assure that the model replicates our findings for both the

[22] Because direct measures of business dynamism are unavailable for these years, we construct the entry rate as the share of firms filing a patent for the first time relative to all firms with a patent history in a given year.

Table 2: Quantification Strategy Initial and Final Balanced Growth Path

Par.	Description	Target	Approach	Value
ψ	R&D cost curvature	R&D cost elasticity	External	2.00
ρ	Discount rate	Risk-free interest rate	External	.020
λ	Innovation step size	Profit share in GDP	External	1.10
η	R&D base capacity	Cross-technology entry	External	1.12
ϕ	R&D productivity scalar	Productivity growth	Indirect inf.	684
ϕ_e	Entry cost scalar	Entrants as % of firms	Indirect inf.	30.4
κ	R&D direction curvature	Patenting specialization	Indirect inf.	1.03
a_0^m	Relative m cost (initial S.S.)	Green share of patents	Indirect inf.	0.995
a_1^m	Relative m cost (final S.S.)	Decline in emissions	Indirect inf.	1.002
T	Duration $a_0^m \to a_1^m$ (years)	Pre-2008 rise green patents	Indirect inf.	73.7
$\nu^{\uparrow}$	Fin. maturity increase prob.	Credit rejection by age	Indirect inf.	.058
$\nu^{\downarrow}$	Fin. maturity decrease prob.	Corner of estimation	Normalized	0
$\overline{\theta}$	Upper bound financial mat.	Commerzbank Diff-in-Diff by age	Indirect inf.	.322
$\underline{\theta}$	Lower bound financial mat.	Pre-2008 young firm green pat.	Indirect inf.	.0052

Notes: See text for details on the numerical values of each of the parameters, and for a summary of the computational algorithm that we use to implement the structural estimation. Parameters estimated by indirect inference are chosen jointly; the target listed next to each is the moment it affects most.

importance of age in green innovation prior to the crisis, and to match the effect of age on exposure to financial shocks in our difference-in-difference regressions. The first two parameters govern the rate at which firms upgrade or downgrade in terms of their financial maturity, $\nu^{\uparrow}$ and $\nu^{\downarrow}$. We discipline them with the age profile of credit constraints in the ECB's Survey on the Access to Finance of Enterprises (SAFE, European Central Bank 2026). Among German firms in 2009–2023, the share of firms whose application for a bank loan was rejected outright is 4.96 times as large for firms firms younger than two years as for firms aged ten years or more.[23]

The model counterpart is the share of firms at the lowest level of financial maturity in each age group, just before the crisis. Because entrants start at the lowest level, this ratio measures how quickly firms grow out of their constraints. Between the lowest and highest levels, a firm's financial maturity improves at an expected rate of $\nu^{\uparrow} - \nu^{\downarrow}$. The effect of age on financial constraints is therefore governed by the gap between the two rates. We therefore normalize $\nu^{\downarrow} = 0$ and calibrate $\nu^{\uparrow}$ to the SAFE ratio, so that $\nu^{\uparrow}$ is the net rate at which firms gain financial maturity. We find a value of $\nu^{\uparrow} = 0.058$.

The second two parameters are the value for θ_i for the least-mature firms ($\underline{\theta}$) as well as the maximum value of $\overline{\theta}$.[24] The lower bound determines how constrained the youngest firms are, and we choose it to match the contribution of below-median aged firms to green innovation prior to the financial crisis (47%, see Figure 6b). As explained in Section 3, this moment drives the relative effect of the financial crisis on innovation in the modern (i.e. green) technology.

[23] We use outright rejection rather than the ECB's broader indicator of financing obstacles because the model's financial maturity is a persistent state. In the panel dimension of the survey, the broader indicator is largely transitory and varies little with age, while persistent constraints fall steeply with age, as outright rejection does. The standard error of the ratio is 0.065.

[24] We specify the grid of θ_i as having N^{θ} equidistance values between these two. We set N^{θ} to 10, which is the highest value for which computation time remained reasonable at the time of writing.

Table 3: Moments in the Data and in the Model for Estimated Parameters

Moment	Data	Model	Parameter
Productivity growth (% per year)	1.50	1.50	ϕ
Entrants as % of firms (per year)	11.4	11.4	ϕ_e
Green share of patents, initial S.S.	0.106	0.106	a_0^m
Decline in non-green product share, final S.S.	0.65	0.65	a_1^m
Green patenting logit regression intercept, first-time patentees	−1.80	−1.80	κ
Green patent share, 2008 relative to 1997	2.20	2.20	T
Young-firm share of green patents, 2008	0.470	0.470	$\underline{\theta}$
Commerzbank effect, green, below-median age	−0.886	−0.886	$\overline{\theta}$
Credit rejection, age < 2 relative to 10+	4.96	4.96	$\nu^{\uparrow}$

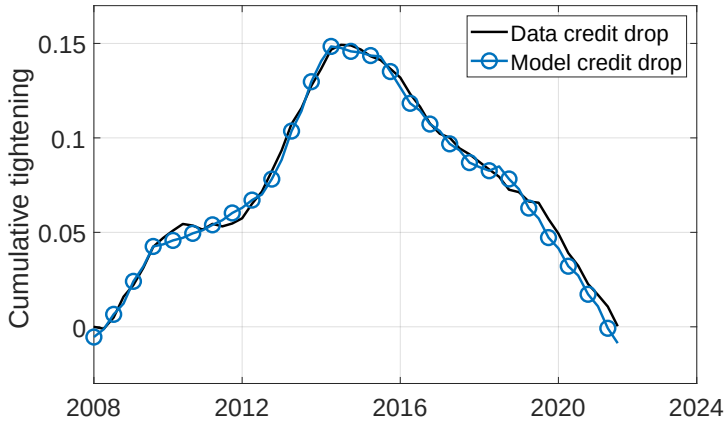
Notes: All moments are targeted and matched jointly; the parameter column lists the parameter each moment affects most (see Table 2).

The upper bound determines how well established firms are shielded when credit tightens, and we choose it to match the response of green patenting to Commerzbank exposure among firms below the median age in Table 1 (−0.886). To compute this response, we tighten the financial constraints of all firms in 2008 by a common factor and measure the immediate change in green R&D of firms below the median age. We choose the size of this tightening so that the model matches the average effect of Commerzbank exposure on green patenting (−0.506).

Computational Implementation To find the parameters of the steady states and the baseline transition between them we deploy the following algorithm. We first guess a vector with values for $\underline{\theta}$, $\overline{\theta}$, $\nu^{\uparrow}$ and T. For each guess, we solve the model for the initial steady state and choose ϕ, ϕ_e, κ and a_0^m to match growth, entry, the green share of patents and the logit intercept, and find the change in a^m that delivers the targeted decline in polluting production. We then solve for the transition using a shooting algorithm, and collect the moments for the financial parameter calibration in 2008: the young share of green patenting, the rise in green patenting, the age profile of credit rejection, and the response of young firms to the Commerzbank shock, after setting the size of that shock and the age gap described above. We then compare these moments to the targets, and iterate until complete. With four parameters and four targets, the model matches every target to within 0.001. We estimate the model on a coarse grid of firm states and then re-solve both steady states on the full grid, which changes the inner parameters by less than 0.3%. Further details on computation of the equilibrium and the transition are provided in Appendix C. Table 2 lists the resulting parameter values.

Shock to Credit Having estimated the model's key parameters, we now summarize our approach to disciplining the shock to credit following the Global Financial Crisis. Our objective is to find the path of aggregate credit conditions, Θ_t in equation (5), so that the model replicates the decline in credit supply during the crisis. A key identification challenge of the tightening of credit conditions is that the Global Financial Crisis and the subsequent Euro

Figure 8. Tightening of Lending Supply in Model and Data



Notes: Implied tightening of credit supply from the ECB Lending Standards Index (Altavilla et al. 2019).

area created a deep recession, that affected both supply and demand for credit. This means that data on new loans issued or loans outstanding are not suitable for our calibration.

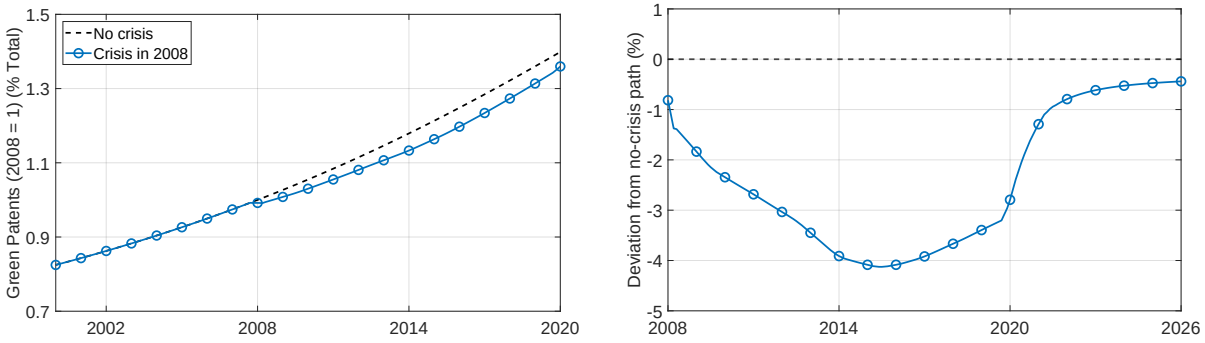
To isolate the change in credit that is due to a tightening of lending conditions, we use the Lending Supply Indicator developed by Altavilla et al. (2019) at the European Central Bank. They aggregate data from bank-level surveys on changing in lending standards into a single index, and we use fitted values of changes in credit outstanding on a regression of this indicator as our target for lending. The black-solid line in Figure 8 presents the implied reduction in credit outstanding from 2008 to 2022. It shows that credit standards caused a gradual reduction of loan supply in the Euro area, which peaked around 2013. In subsequent years there was a gradual easing of credit, reaching baseline values around 2022. The blue-circled line shows that our calibration for the path of Θ_t induces a closely matched path of credit tightening. In the quantitative experiment of the subsequent section, we allow Θ_t to remain at its steady state value of unity from 2022 onwards.

4.3. Results

With the quantified model in hand, we turn to a final counterfactual exercise: if we simulate a tightening of financial constraints large enough to match Figure 8, can the self-selection of young firms into green technologies during the transition explain a meaningful part of the slowdown in green patenting that we observe in the data? And how long does the effect of such a patenting slowdown on the mix of good production persist?

Effect on green patenting Figure 9 plots the relative effect of the financial crisis on green innovation. In the left-hand figure, the blue-circled line plots the share of new patents directed toward the green technology, normalized to 1 at the onset of the financial shock. The black dashed line shows the counterfactual path of that share in the absence of a financial

Figure 9. Effect of a Financial Shock in 2008 on Green Patenting



(a) Index of Green Patenting Share

(b) Deviation from No-Crisis Path

Notes: Panel (a) in the figure plots the share of green patents in total patents, with (blue-circled line) and without (black-dashed line) a tightening of financial constraints Θ_t along the path plotted in Figure 8 (2008q3–2021q4). Both lines are normalized by the no-crisis value in 2008.

crisis. In the right-hand figure, we plot the impulse response of the crisis: the percentage gap between the true and the counterfactual path of green innovation.

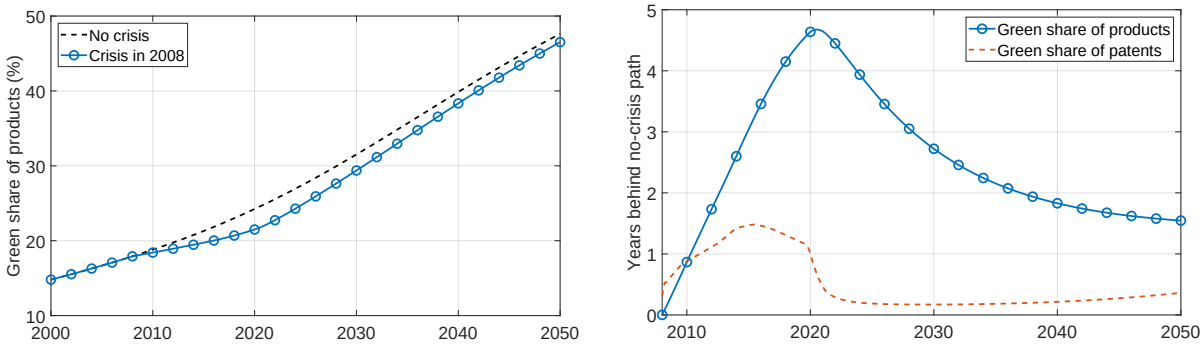
Without the crisis, the green share of patenting would have risen by 18% between 2008 and 2014, continuing its pre-crisis trend. With the crisis, it rises by only 13%: the crisis erases about a fifth of the rise in green patenting over this period, and by 2014 the green share is 3.9% below its no-crisis path. Measured in time, green patenting falls 1.5 years behind its no-crisis path by 2015. The driver of this result is firm age: one year into the crisis, the innovation rate of firms at the lowest level of financial maturity is 48% below its no-crisis path, and entry falls by half. Mature firms are much less affected and in fact innovate 6% *more*, because the decline in entry and in innovation by young firms lowers the rate of creative destruction and so raises the value of owning a product line. This mirrors the age gradient in the response to Commerzbank exposure in Table 1. Because young firms account for a larger share of green than of non-green innovation, the same tightening slows green innovation by more than non-green innovation.

On impact, the model predicts a flattening of the green patent share, closely resembling the slowdown in green innovation visible in both the German and global patent series (Figures 6 and 1). One difference is that the model generates an immediate effect of the shock on patenting. This is because the shock immediately lowers the Poisson arrival rate of ideas. If we instead impose a lag of, say, three to five years between R&D investment and innovation, the timing lines up well with the data.[25]

Over longer horizons, the self-selection of young firms into new technologies explains a smaller share of the path of green patenting. Once credit conditions normalize in the early 2020s, the green patent share returns to within a few months of its no-crisis path. In the data, by contrast, green patenting remains subdued until the late 2010s. That the model does not

[25] Such a lag is consistent with a large empirical literature on the delay between R&D and innovation, going back going back to Pakes and Griliches 1980. They find a lag of up to 5 years between investments and patenting.

Figure 10. The Crisis Delays the Green Transition in Production



(a) Green share of products (b) Years behind the no-crisis path

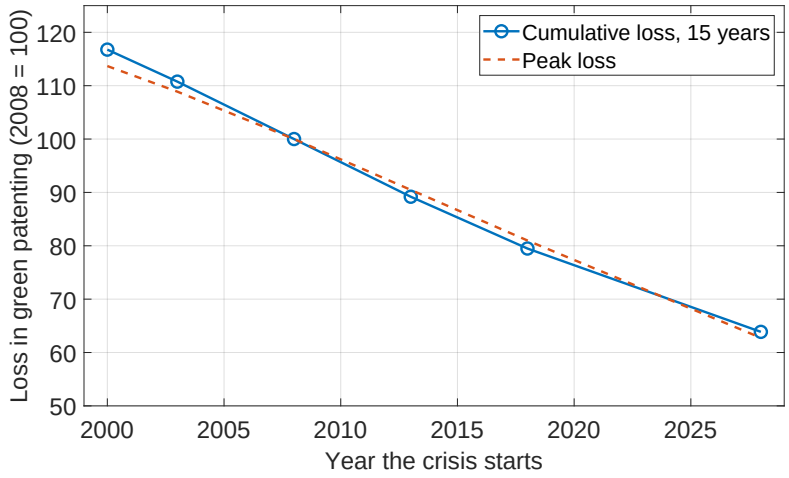
Notes: Panel (a) plots the share of product lines produced with the green technology, with (blue-circled line) and without (black-dashed line) the financial crisis of Figure 9. Panel (b) plots the number of years by which the crisis path lags the no-crisis path: for each date, the time it took the no-crisis economy to reach the value that the crisis economy attains at that date. Blue-circled line: green share of products. Orange-dashed line: green share of patents (Figure 9).

account for the entire decline is not surprising. The mechanism we study is not the only force shaping green innovation after 2008, and the post-crisis macroeconomic environment changed along several other dimensions that likely mattered as well. Examples include the rise of shale gas, sharp decline in energy prices after 2007 and cuts to European green subsidies during the austerity period (Hofman and Huisman 2012). Other financial forces may also have played a role, such as shifts in investor demand for green innovation or changes in risk appetite and regulation. The point of Figure 9 is therefore not that financial constraints explain the whole slowdown. It is that, holding these other forces constant, the self-selection of financially constrained young firms into green innovation accounts for a meaningful share of it.

Persistent effects on green production Turning to the crisis' effects on the use of green and non-green technology in production, we see that the temporary shortfall in green patenting has long-lived effects on the mix of production. Figure 10a plots the share of product lines produced with the green technology. Its growth slows sharply after 2008, and by 2020 it stands at 21.5% instead of 24.2%, 11% below its no-crisis path. Figure 10b expresses this gap in time. While green patenting is at most 1.5 years behind its no-crisis path and catches up once credit conditions normalize, the green transition in production falls further behind throughout the crisis, reaching a delay of 4.7 years in 2020. Because the foregone green innovations add up over time, the delay unwinds only slowly: in 2040, three decades after the crisis began, the green share of production is still 1.8 years behind. A temporary tightening of credit thus has a long-lasting effect on the pace of the transition.

Counterfactual effect of crisis timing In a final exercise of the application, we ask what the effect of a financial crisis at different points in the transition would have been. A central

Figure 11. Counterfactual: The Timing of the Financial Crisis and Green Patenting



Notes: Each point is a simulation in which the path of Θ_t of Figure 8 starts in the year on the horizontal axis, with the transition starting in 1998. Blue-circled line: cumulative shortfall of the green share of patenting relative to the no-crisis path over the first 15 years of the crisis. Orange-dashed line: largest shortfall. Both are normalized to 100 for a crisis starting in 2008.

implication of the theory is that the cost of financial crises is state dependent: crises are more damaging when the economy is in the early stages of a technological transition. If a crisis arrives later in the transition, firms with a comparative advantage in the new technology have had more time to mature and are therefore less financially constrained. The same logic applies to the German transition to green technology that we quantify the model to.

Figure 11 illustrates this by subjecting the economy to financial crises that follow to the same path for Θ_t, but that vary in the year in which the crisis starts. The blue-circled line plots the cumulative loss in green patenting over the first 15 years of the crisis, and the orange-dashed line plots the largest shortfall, both relative to a crisis starting in 2008. The cost of the crisis falls steadily the later it arrives. Had the Global Financial Crisis occurred five years later, in 2013, the loss in green patenting would have been 11% smaller. A crisis in 2000, at the start of the transition, would have been 17% more costly, and a crisis in 2028 36% less costly. In terms of the peak effect, the green patent share falls by 4.7% below its no-crisis path for a crisis in 2000, by 4.1% for the actual crisis, and by 2.6% for a crisis in 2028.

5. Conclusion

This paper proposes that new technology vintages are disproportionately affected by financial disruptions when the economy is in transition towards a new technological steady state. We hypothesize that younger firms have an endogenous comparative advantage in innovation in emerging technology vintages at the early stages of a transition, as unlike older firms they have not accumulated expertise in mature technology vintages. As young firms are financially constrained, a tightening of overall credit will thus endogenously affect innovation in new technology vintages more than innovation in mature ones.

We develop this argument using a Schumpeterian growth model with firm dynamics where: (i) firms expand their portfolio of products by engaging in innovation directed at either modern or old technology vintages in order to improve existing product lines; (ii) the choice between modern or old vintage innovation is path dependent, in the sense that it becomes increasingly less costly for a firm to innovate in a given vintage if they already produce a large number of products using that vintage; (iii) firms are subject to credit constraints that depend on their age, with younger firms facing the tighter constraints.

Our main finding is that a financial crisis has a state-dependent effect on innovation in new technologies. As there is no intrinsic difference between financing costs of innovation directed at modern versus old vintages, both would be equally affected in the steady state. This changes during a transition towards modern vintages, when young firms disproportionately carry innovation in the new direction.

We validate these mechanisms using micro evidence on green patenting by German firms around the Global Financial Crisis. We exploit firms' pre-crisis dependence on Commerzbank—a large German bank that cut its lending stock by 35% after incurring severe subprime losses—as plausibly exogenous variation in credit tightening. We document three facts consistent with the model's predictions. First, young firms accounted for a disproportionate share of green patenting prior to the crisis—around 45% of green patents versus only 17% for non-green patents. Second, Commerzbank exposure significantly reduced green patenting in subsequent years, with an elasticity of around 3 by 2018, while leaving non-green patenting unaffected. Third, this asymmetric effect is driven entirely by young firms, who cut both green and non-green patenting sharply in response to tighter credit, while older firms are unaffected.

Quantifying the Schumpeterian framework to match the rise of green patenting in the years prior to the Global Financial Crisis, we simulate the effect of a tightening of credit constraints early in the transition. We find that the decline in credit induced by the financial crisis is able to explain about a fifth of the slowdown in green patenting after 2008, and that the self-selection of younger firms into green technology slowed the transition down by around five years.

Although our application has focused on green innovation as a canonical transition hit by the Global Financial Crisis, our theoretical set-up is applicable to other technological paradigm shifts. Historically, the persistent role of financial crises on economic outcomes (Reinhart and Rogoff 2014) may be due to the mechanism we describe here, due to the slowdown of start-up innovation reducing productivity growth. Looking ahead, a financial shock may severely slow the technological transition associated with AI. These are exciting areas for future work.

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Appendix A. Theoretical Appendix

A.1. Derivations of the Aggregate Variables

To find the equilibrium wage, start from the expression for aggregate output:

$$\ln Y = \int_0^1 \ln q_j + \ln y_j dj,$$

where firm subscripts are omitted for readability. Inserting unit-elastic demand gives:

$$\ln Y = \int_0^1 \ln q_j dj + \ln Y - \int_0^1 \ln p_j dj,$$

Note that the unit measure of products can be separated into the fraction F that is produced with the new technology vintage, and the remainder $1-F$ which is produced with the old technology vintage:

$$\ln Y = \int_0^1 \ln q_j dj + \ln Y - \int_0^F \ln p_j dj - \int_F^1 \ln p_j dj.$$

Further note that, by the law of large numbers, a fraction F of all products is produced with a new technology second-best competitor, regardless of whether the first-best (producing) firm uses the new or old technology vintage itself. Inserting optimal prices using the values for marginal costs and markups (2) therefore yields

$$0 = \int_0^1 \ln q_j dj - F\ln(w/a^m) - (1-F)\ln w - F\left(F\ln(\lambda) + (1-F)\ln(\lambda a^m)\right) - (1-F)\left(F\ln(\lambda/a^m) + (1-F)\ln(\lambda)\right)$$

Isolating w on the left-hand side and grouping terms yields (13).

Next we derive an expression for aggregate output from the resource constraint. Define L^p as the total amount of labor devoted to goods production. Labor market equilibrium requires

$$L^p = \int_0^1 l_j dj$$

where, again, firm subscripts are omitted. Inserting production and demand functions yields

$$L^p = \int_0^F y_j/a^m dj + \int_F^1 y_j dj \quad \Rightarrow \quad L^p = Y\left(\int_0^F (p_j)^{-1}/a^m dj + \int_F^1 p_j^{-1} dj\right)$$

Inserting optimal prices gives

$$L^p = \frac{Y}{w}\left(F\left[F/\lambda + (1-F)/(\lambda a^m)\right] + (1-F)\left[Fa^m/\lambda + (1-F)/\lambda\right]\right)$$

Inverting the function and inserting the equilibrium wage (13) yields

$$Y = L^p \exp\left(\int_0^1 \ln q_j dj\right)\left(\frac{\left(\exp\left(\overline{\ln \mu^m}\right)^F \exp\left(\overline{\ln \mu^o}\right)^{(1-F)}\right)^{-1}}{F\left[F/\lambda + (1-F)/(\lambda a^m)\right] + (1-F)\left[Fa^m/\lambda + (1-F)/\lambda\right]}\right)(a^m)^F$$

The term in large brackets is $\mathcal{W}$ iin the main text: the geometric mean of inverse markups divided by their arithmetic mean, so that $\mathcal{W} \leq 1$. Production labor follows from labor market clearance (16), $L^p = L^m + L^o = 1 - L^{rd} - L^e$.

A.2. Proof of Proposition 1

We first establish the scaling of firm values along a balanced growth path. On such a path, aggregate output Y_t and wages w_t grow at the common rate g, while all arrival rates, markups, product shares, and financial-transition rates are constant. Product flow profits are proportional to aggregate income: a product produced with vintage $h \in \{m, o\}$ against a closest competitor of vintage h' yields flow profit $\pi^{hh'}Y_t$. Hence the value of any product line must also scale with Y_t. Writing

$$V_t(J, \theta) = Y_t v(J, \theta),$$

and using $\dot{Y}_t/Y_t = g$, we have

$$\dot{V}_t(J, \theta) = gV_t(J, \theta)$$

whenever the normalized value $v(J, \theta)$ is time invariant, as it is on the balanced growth path.

We next use the fixed-cost normalization in the text. The fixed operating cost $F(J, \theta)$ is chosen to absorb the residual option value of R&D that arises from firm size, technological composition, and financial maturity. The remaining value of a firm is therefore the sum of the values of the product lines it currently operates. Thus

$$V_t(J, \theta) = (n^m V^m + n^o V^o)Y_t. \tag{10}$$

Here V^h is the normalized present value of owning one product line produced with vintage h, taking expectations over the vintage of the closest competitor. For example, if a fraction F of products is produced with the modern vintage, the expected flow profit from a modern product is

$$\bar{\pi}^m = F\pi^{mm} + (1-F)\pi^{mo},$$

and analogously

$$\bar{\pi}^o = F\pi^{om} + (1-F)\pi^{oo}.$$

Since each product line is displaced at rate τ, these product values satisfy

$$(r - g + \tau)V^h = \bar{\pi}^h, \qquad h \in \{m, o\}.$$

This verifies that V^m and V^o are time invariant on the balanced growth path.

It remains to characterize optimal R&D. Let

$$A(x^m, x^o) \equiv (x^m)^\kappa (N^m)^{1-\kappa} + (x^o)^\kappa (N^o)^{1-\kappa}.$$

The incumbent R&D cost is

$$rd_i(x^m, x^o) = \frac{\phi}{\psi} N^{1-\psi/\kappa} A(x^m, x^o)^{\psi/\kappa}.$$

Because R&D must be financed in advance, the borrowing constraint is equivalent to a constraint on R&D expenditure. Let $\mathcal{M}(J,\theta) \geq 0$ denote the multiplier on that constraint, expressed as a wedge on the marginal cost of R&D. The first-order condition for innovation directed to vintage h is therefore

$$YV^h = w(1 + \mathcal{M}(J,\theta))\phi N^{1-\psi/\kappa} A^{\psi/\kappa - 1} (x^h)^{\kappa-1} (N^h)^{1-\kappa}.$$

Hence

$$x^h = K(V^h)^{1/(\kappa-1)} N^h,$$

where K is common across the two innovation directions. Substituting back into A gives

$$A = K^\kappa S(J), \qquad S(J) \equiv (V^m)^{\kappa/(\kappa-1)} N^m + (V^o)^{\kappa/(\kappa-1)} N^o.$$

Using this expression in the first-order condition yields

$$K^{\psi-1} = \frac{Y}{w} \frac{1}{\phi N^{1-\psi/\kappa} S(J)^{\psi/\kappa - 1} (1 + \mathcal{M}(J,\theta))}.$$

Therefore

$$x^h(J,\theta) = \left(\frac{Y}{w} \frac{1}{\phi N^{1-\psi/\kappa} S(J)^{\psi/\kappa - 1} (1 + \mathcal{M}(J,\theta))} \right)^{1/(\psi-1)} (V^h)^{1/(\kappa-1)} N^h. \tag{11}$$

By complementary slackness, $\mathcal{M}(J,\theta) = 0$ when the financing constraint is slack, and otherwise declines weakly with financial maturity θ.

Finally, the entrant problem is identical except that $N_e = \eta^m + \eta^o$, the relevant experience terms are η^m and η^o, and the R&D cost shifter is ϕ_e. Defining

$$S_e \equiv (V^m)^{\kappa/(\kappa-1)}\eta^m + (V^o)^{\kappa/(\kappa-1)}\eta^o,$$

the same steps imply

$$e^h = \left(\frac{Y}{w}\frac{1}{\phi_e N_e^{1-\psi/\kappa} S_e^{\psi/\kappa-1}(1+\mathcal{M}_e)}\right)^{1/(\psi-1)} (V^h)^{1/(\kappa-1)}\eta^h. \tag{12}$$

Appendix B. Empirical Appendix

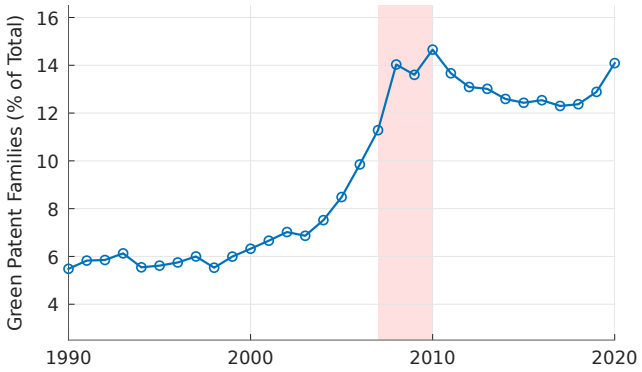
B.1. Additional figures and tables

Table B1: Descriptive Statistics

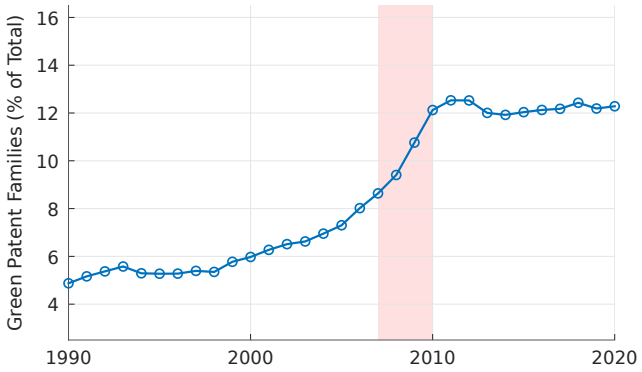
	Mean	St. Dev.	Median	10th Pct.	90th Pct.
Value added	73,384,421	6.14E+08	11,249,385	3,342,691	97,015,680
Employment	969	10,832	144	35	1,145
Operating Profits	73,384,413	6.14E+08	11,249,381	3,342,692	97,015,688
Fixed Assets	61,749,246	6.2E+08	6,091,660	622,625.9	96,746,492
Wage Bill	28,111,845	2.72E+08	3,912,469	1,055,326	36,397,191

Notes: Summary statistics for the merged Dafne-Creditreform-Patstat dataset. Our dataset starts from the sample in Huber (2018) but extends it with additional patent data up to 2020.

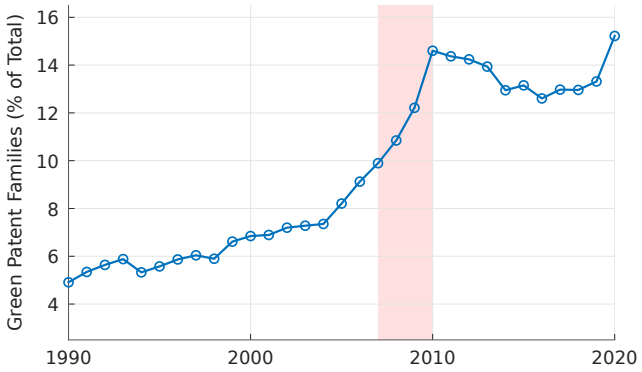
Figure B1. Alternative Trends in Green Patents as a Percentage of Total Patents



(a) Citation-Weighted



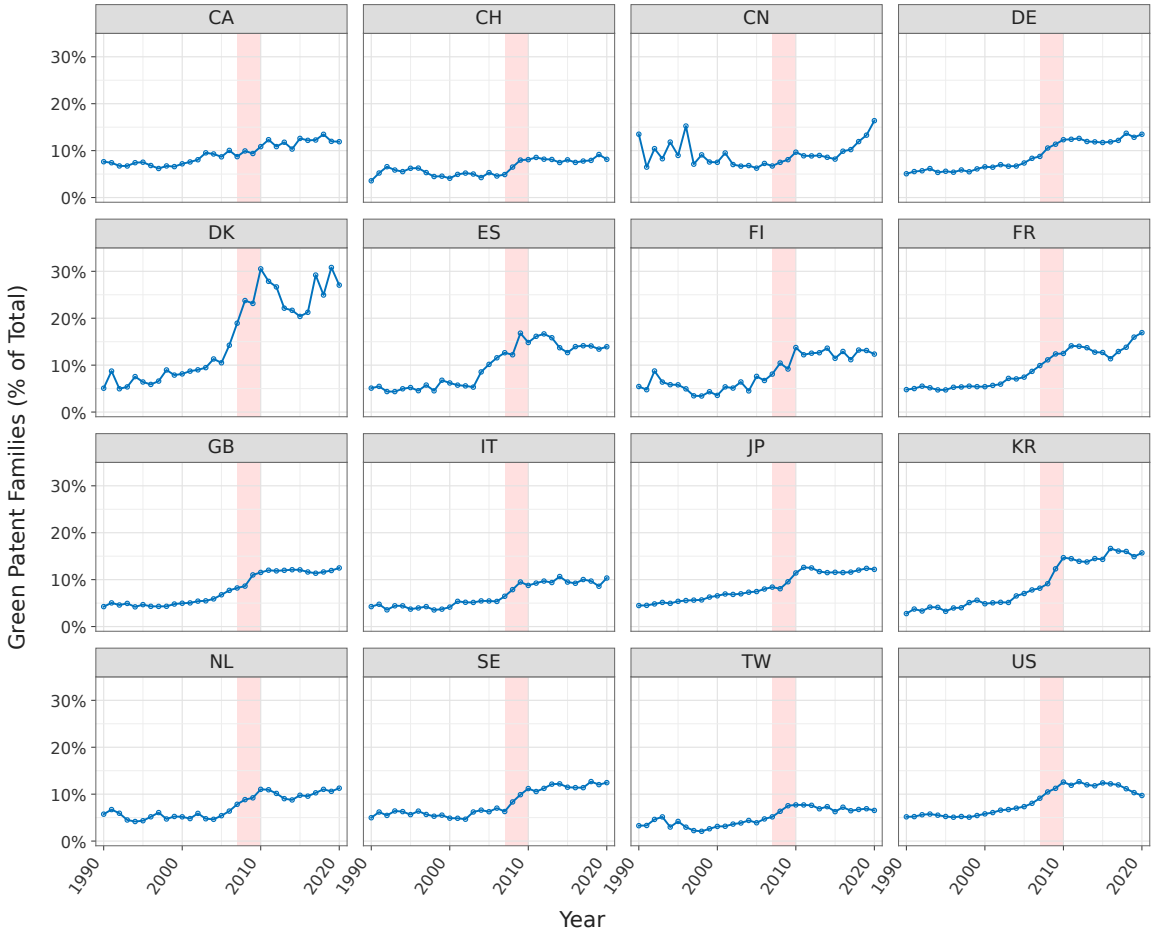
(b) OECD



(c) Triadic

Notes: The figure shows annual shares of green patent families over 1990–2020. Families are dated by their earliest filing year and classified as green if at least one member has a CPC Y02 classification, covering climate-change mitigation and adaptation technologies. Panels (a) and (b) include invention-patent families with filings at two or more patent offices and at least one observed grant; PCT publications do not count as an additional office. Panel (a) weights families by the number of distinct other families citing them within five years of their earliest filing date; uncited families receive zero weight. Panel (b) restricts the sample to families with at least one assignee located in an OECD country, using membership at the end of 2020 and the earliest family record with usable residence information. Panel (c) includes families with filings at the European Patent Office, the US Patent and Trademark Office, and the Japan Patent Office, regardless of grant status. The shaded area covers 2007–2010. Source: national and regional patent-office records accessed through Google Patents Public Data; authors' calculations.

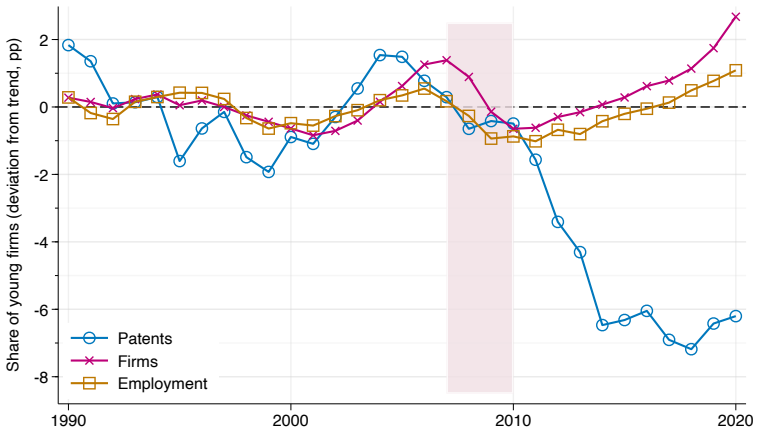
Figure B2. Global Trend: Green Patents as a Percentage of Total Patents



Notes: The figure shows the annual share of green patent families by inventor country of residence over 1990–2020. As in Figure 1, the sample includes invention-patent families with filings at two or more patent offices and at least one observed grant; PCT publications do not count as an additional office. Families are dated by their earliest filing year and classified as green if at least one member has a CPC Y02 classification, covering climate-change mitigation and adaptation technologies. Each family is allocated fractionally across countries according to its inventors' recorded residence, using the family record with the earliest filing date among those with usable residence information. The same weights enter the green-family numerator and total-family denominator. Inventors with missing residence retain an unallocated share of the family weight. The shaded area covers 2007–2010. Source: national and regional patent-office records accessed through Google Patents Public Data; authors' calculations.

CA: Canada; CH: Switzerland; CN: China; DE: Germany; DK: Denmark; ES: Spain; FI: Finland; FR: France; GB: United Kingdom; IT: Italy; JP: Japan; KR: Republic of Korea; NL: Netherlands; SE: Sweden; TW: Taiwan; US: United States.

Figure B3. Share of patents, firms and employment from young firms



Notes: . The orange dashed line reports the share of firms younger than 15 years, while the blue dashed line reports the share of total employment in firms younger than 15 years. Each raw series is detrended using data over the 1990–2006 period. Source: Census' Business Dynamic Statistics

B.2. Defining Emerging vs. Old Technologies

In this Appendix, we describe the construction of the data presented in Figure 2. We consider USPTO patents (kind codes B1, B2 and A) from 1976. Each technology is a *substitution pair*: a patent is either counted as *new* if any of its CPC subgroups falls under the "new" code set and as *old* if it falls under the "old" set, the two sets being defined by CPC prefixes in Table B2. A patent matching both code sets is assigned to the new technology. For each filing year, we count distinct patents and form the share of new technologies (relative to the sum of new and mature technologies) $f_t = N_t^{\text{new}}/(N_t^{\text{new}} + N_t^{\text{old}})$, smoothed with a three-year centered moving average. The series start in 1990, except when not enough patents are available for the new technology. We consider the following eight examples.

- **Agricultural biotechnology.** Agricultural biotechnology improves crops through genetic engineering and modern molecular breeding, particularly through genetically modified seeds that are resistant to pests or drought. The old category covers conventional agricultural technologies, including mechanical equipment, fertilizers, and chemical pesticides.

- **Electric vehicles.** Electric vehicles are powered by an electric motor driven by a battery, without an internal combustion engine. The old technology is the internal combustion engine, which has been used in cars for over a century.

- **Coherent optical.** Coherent optical transmission uses sophisticated digital signal processing to carry a much larger volume of data over fiber-optic cables, which carry Internet traffic between cities and continents. Old technology relies on simpler direct-detection optical links and older electrical (copper) links.

- **Peer-to-peer networking.** Peer-to-peer (P2P) networks allow computers to exchange files and content directly with one another, without going through a central server. The old technology is the client-server model, in which each user connects to a website or central server.

- **Self-driving vehicles.** Self-driving systems let a vehicle sense its surroundings and control steering, braking and acceleration on its own. The incumbent category covers conventional steering and braking systems.

- **Solar photovoltaic panels.** Solar photovoltaic panels convert sunlight directly into electricity using semiconductor cells. The incumbent category covers conventional thermal power-generation technologies, including steam and gas turbines. The corresponding CPC codes cover fossil-fuel generation, but are also wider than this.

- **Stem cells.** Pluripotent stem cells can become any cell type in the body, a foundation for regenerative medicine. They include embryonic stem cells and induced stem cells reprogrammed from ordinary adult cells. The incumbent is conventional cell culture using already-specialized cells. We exclude immune cells (T/B/NK cells) from the comparison, because the recent CAR-T cancer-immunotherapy boom is a separate new technology that would otherwise inflate the old technology group.

- **Turbocharging.** A turbocharger reuses the engine's hot exhaust to push extra air into the cylinders, so a small engine can deliver the power of a larger one ("engine downsizing"). The incumbent technology is a conventional naturally aspirated engine that draws in air unaided.

Table B2: CPC classification rules (prefix match on current-scheme subgroups)

Technology	New (emerging)	Old (incumbent)
Agricultural biotechnology	A01H; C12N15/82	A01B, A01C, A01D, A01M, A01N
Electric vehicles	B60L	F02
Coherent optical	H04B10/60, /61	H04B10/12, /25, /40; H04B3
Peer-to-peer	H04L67/104, /06, /108	H04L67/02, /1001; H04L69/329
Self-driving	B60W60, /30, /40, /50	B62D, B60T
Solar PV	H02S	F01K, F02C, F01D, F23
Stem cells	C12N5/0696, /0606	rest of C12N5/06 (excluding C12N5/0634, /0636, /0638, /0639, /0645, /0646)
Turbocharging	F02B37, F02B39	F02B23, /25, /27, /29, /31, /75; F02F1, F02F3; F02D9; F02M35

B.3. Additional Evidence on Young Technologies and Financial Conditions

To provide broader evidence of the disproportionate effect of the Global Financial Crisis on innovation in emerging technologies, this appendix shows that average young-technology patenting fell behind its pre-crisis predicted path across technologies. There are two changes compared to the analysis of the examples in Figure 2. First, we include all CPC subclasses, which is possible because we do not have to match every emerging technology to a mature technology that it replaces. Second, our outcome variable of interest is the share of all patents in a technology relative to a predicted pre-crisis path of this share, to account for the fact that the rise of patenting in emerging technologies tapers off at some point regardless of whether the economy experiences a financial crisis (Ribeiro 2026).

Our outcome variable of interest is defined as follows. Let $n_{c,t}$ denote the patent count for CPC subclass c in year t, and let $N_t = \sum_{c \in C} n_{c,t}$ be the sum of these counts across all subclasses in the input panel, before the regression sample restrictions. We define the technology-year patent share as $S_{c,t} = n_{c,t}/N_t$ and the five-year lag moving average as $\widetilde{S}_{c,t} = \frac{1}{5}\sum_{j=0}^{4} S_{c,t-j}$. As in Figure 2, we use patent *shares* to net out aggregate changes in the level of patenting.

In the regression, we compare true patenting to a fitted path. We obtain that path by estimating, separately for each technology, a parametric *Gompertz level* curve as a function of technology age. Parametric diffusion curves provide a standard reduced-form representation of technological development (Geroski, 2000; Griliches, 1957; Ribeiro, 2026). Letting a denote age, we model the smoothed patent share as

$$g(a; K, b, m) = K \exp\Big(-\exp\big(-b(a-m)\big)\Big), \qquad K \in [0,1],\ b \in [10^{-6}, 10],\ m \in \mathbb{R},$$

where K is the asymptotic share, b governs the speed of growth, and m is the age at the inflection point. We estimate (K_c, b_c, m_c) by nonlinear least squares using the eleven annual observations from ages 0–10, and define $\widehat{S}_{c,t} = g(a_{c,t}; \widehat{K}_c, \widehat{b}_c, \widehat{m}_c)$. Thus $\widehat{S}_{c,t}$ describes the fitted evolution of a technology's patent share based on its early-life trajectory.

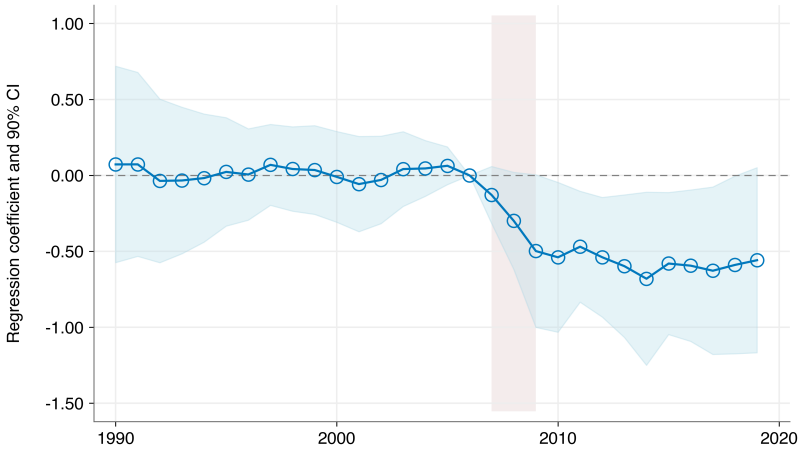
We define the "birth" of a technology, $t_{0,c}$, as the first year of three consecutive years in which the cleaned subclass patent count is at least 20. Next, we compare realized patent shares relative to their fitted paths across young and mature technology classes. Specifically, we estimate

$$R_{c,t} \equiv \frac{\widetilde{S}_{c,t}}{\widehat{S}_{c,t}} = \sum_{\tau \neq 2006} \beta_\tau \, \mathbb{I}_{t=\tau} \, \text{Young}_c + \psi_c + \chi_t + \eta_{a_{c,t}} + \varepsilon_{c,t}, \tag{B1}$$

where Young_c indicates a young technology class at the time of the crisis ($1990 \leq t_{0,c} \leq 2000$), ψ_c and χ_t denote technology and year fixed effects, and $\eta_{a_{c,t}}$ are technology-age fixed effects.

Figure B4 reports the estimated coefficients β_τ with 90% confidence intervals. The pre-crisis estimates are close to zero. The post-2008 point estimates are negative, indicating that realized-to-fitted patent shares declined more in young than in mature technologies.

Figure B4. Young versus Mature Technologies Around the Global Financial Crisis



Notes: The unit of observation is a CPC4 technology-year. The dependent variable is $R_{c,t} = \widetilde{S}_{c,t}/\widehat{S}_{c,t}$, where $\widetilde{S}_{c,t}$ is the backward-looking five-year average of the patent share and $\widehat{S}_{c,t}$ is obtained by fitting a Gompertz level curve on ages 0–10. The regression is weighted by patent counts summed over ages 0–10 and includes CPC4, year, and age fixed effects; 2006 is the omitted year. Standard errors are clustered at the CPC4 level. The displayed 90% confidence intervals are the coefficient plus or minus 1.65 standard errors, conditional on the fitted paths. The main estimation covers 1990–2019 and retains observations with nonnegative age and finite ratios for subclasses with $1950 < t_{0,c} \leq 2000$. Regressions are weighted by each subclass's total patent count over ages 0–10.

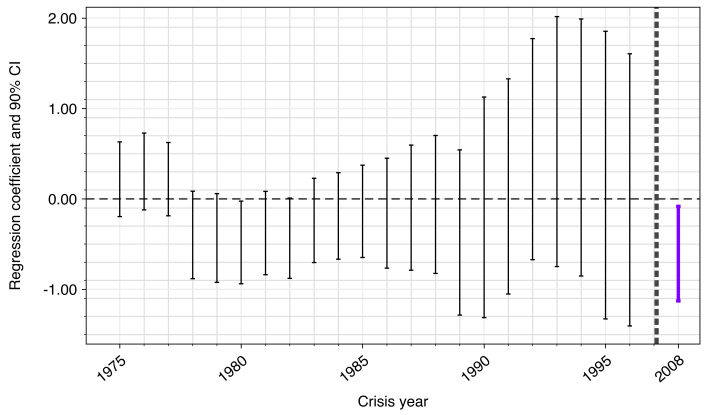
Although the confidence intervals are wide, this is consistent with the case studies of specific technological transitions documented in Figure 2.

As a validation exercise, we assess whether this pattern is specific to 2008. To do so, we repeat the event study using placebo crisis dates between 1975 and 1996. For each placebo date E, we re-estimate the regression using the same fitted paths, with an estimation window from $E-18$ to $E+11$ and reference year $E-2$. We retain subclasses with $1930 < t_{0,c} \leq E-8$ and define young subclasses by $t_{0,c} \geq E-18$, applying the same weighting and selection rules. We summarize the medium-run effect by averaging the coefficients from crisis+6 to crisis+11 (corresponding to 2014–2019 for the actual crisis).

Figure B5 plots the results. The horizontal axis plots the year of the (placebo) crisis, while the vertical axis plots the average post-crisis β. As expected, the estimate for 2008 lies at the negative end of this distribution. For other placebo dates, although the estimated coefficients are insignificant, their estimates correlate intuitively with the state of financial conditions in the year considered. Figure B6 illustrates this pattern by plotting the placebo estimates against the Chicago Fed's National Financial Conditions Index. The association is clearly negative: episodes of tighter financial conditions are associated with a more negative subsequent gap for young technologies.

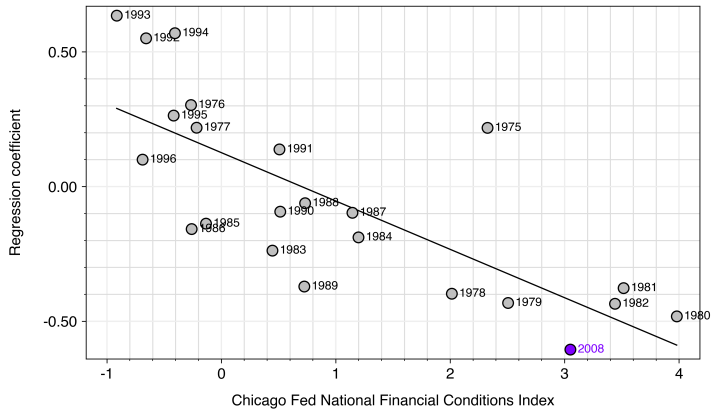
The results in this Appendix are consistent with financial conditions contributing to the differential evolution of emerging technologies. We place less weight on them than the case studies in Figure Figure 2 in the main paper, due to the inherent difficulty of describing counterfactuals for the evolution of emerging vs. mature technologies across the whole economy.

Figure B5. Placebo Crisis Dates and Medium-Run Effects on Young Technologies



Notes: This figure reports a placebo exercise based on equation (B1). For each placebo crisis year between 1975 and 1996, we re-estimate the event-study specification treating that year as the crisis date, and compute the average of the estimated coefficients β_τ from placebo+6 to placebo+11. The figure also reports the corresponding estimate for the actual 2008 Global Financial Crisis. A more negative value indicates a larger post-crisis decline in the realized-to-fitted patent-share ratio for young relative to mature technologies. The bars show 90% confidence intervals, computed as the estimated mean plus or minus 1.65 clustered standard errors using the full covariance matrix of the six coefficients.

Figure B6. Correlation Between Placebo Coefficients and Financial Conditions



Notes: This figure plots the placebo estimates from Figure B5 for each crisis year against the annual maximum of the Chicago Fed's weekly National Financial Conditions Index. Higher values correspond to tighter financial conditions. The line is an ordinary least-squares fit through all displayed dates, including 2008.

Appendix C. Computational Appendix

This appendix summarizes the computational algorithm used in the quantitative exercise. The firm-level state is (n^m, n^o, θ), where n^m and n^o denote the number of modern and old product lines and θ indexes financial maturity. The same state space is used in the stationary equilibrium, in the transition problem, and in the auxiliary firm-level simulations.

1. *Steady states and structural estimation.*

   (a) Computation starts from a set of structural parameters, numerical settings, and empirical targets. These objects determine the moments targeted in the initial steady state, the emissions-reduction target used to discipline the final steady state, the length of the transition horizon, and the financial shock in the crisis.

   (b) The initial steady state is estimated by nonlinear least squares over $(\phi, \phi_e, \kappa, a_0^m)$. For each candidate parameter vector, the model is solved and the resulting moments are compared with their targets. The moments used in this stage are the entry rate, the growth rate, the green share of patents, and the green logit intercept for first-time patentees.

   (c) Each evaluation of the objective requires solving the stationary equilibrium as a nonlinear system in the aggregate equilibrium objects, such as the values V^m and V^o, the rate of creative destruction τ, and the modern share F. The inner fixed point works as follows:

      i. Given a guess for the aggregate equilibrium objects, compute state-by-state innovation rates for all firm states. The R&D first-order conditions are solved analytically. Unconstrained states use the closed-form interior solution, while constrained states use the closed-form solution associated with a binding financial budget, so no nested state-by-state nonlinear solver is required.

      ii. Construct the sparse transition matrix for firm dynamics over all active states and the exit state. This matrix incorporates product gains, product losses, movements across financial-maturity states, exit after the last product is lost, and entry at the lowest financial-maturity state.

      iii. Recover the stationary distribution by solving

$$\begin{bmatrix} T \\ \mathbf{1}' \end{bmatrix} M = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

      iv. Aggregate the resulting distribution to obtain entry, aggregate innovation, labor allocations, the modern-product share, growth, and R&D intensity.

      v. Return the associated residuals of the equilibrium equations under the guesses and iterate until the system converges.

(d) After the initial steady state has been estimated and solved, we calculate F and use it to find the target increase for the final steady state. The final steady state is then estimated by a nonlinear least-squares problem over a_1^m, so that the model matches the final modern-share target implied by the emissions-reduction objective.[26]

2. *Transition, financial parameters, and crisis computation.*

(a) Once the initial and final steady states have been solved, the transition algorithm builds a finite time grid with step size Δt. The path for a^m is then parameterized as a sigmoid, so that a^m moves gradually from its initial to its final value over T years.

(b) The duration T and the financial parameters $\underline{\theta}$, $\overline{\theta}$ and $\nu^{\uparrow}$ are estimated jointly in an outer loop. For each candidate, we re-estimate both steady states as above, solve the no-shock transition, and compute the moments in 2008: the young share of green patenting, the rise in green patenting since 1997, the age profile of credit rejection, and the response of young firms to the Commerzbank shock. The size of that shock is chosen so that the model matches the average Commerzbank effect in the difference in difference table. We chose the values that minimize the squared gap between these moments and their targets.

(c) The baseline transition without a financial shock is solved as a fixed point over the entire time path using a shooting algorithm. Each iteration has four steps:

i. *Forward pass.* For every date on the grid, compute state-level innovation rates, entry rates, and the period-specific sparse generator, then update the cross-sectional distribution of firms over (n^m, n^o, θ) using the law of motion implied by that generator.

ii. *Aggregation.* Given the updated distribution, compute product shares, markups, wages, output, labor allocations, growth, and R&D intensity date by date.

iii. *Backward pass.* Update the value of old and modern products using backward recursion.

iv. *Update step.* Use the new value-function paths to update the guess for the next iteration. The fixed-point iteration is accelerated with an Anderson step and is repeated until the value functions, output, and wages converge.

(d) The crisis block adds a time-varying financial shock. A quarterly path for the multiplier Θ_t on θ is estimated from lending data by optimizing over a low-dimensional knot parameterization. The optimized knot values are then interpolated to a full quarterly series, mapped into model periods, and, after the calibrated path ends, the multiplier returns to one.

[26] To reduce computation time, the parameter search is performed on a coarse grid of firm states and accelerated through warm starts. However, the final reported estimates are always re-evaluated on the full grid before they are treated as official results.

(e) The crisis transition is then solved using the same fixed-point algorithm, but under imperfect foresight. Before the shock arrives, firms evaluate innovation and entry decisions using the no-shock transition as the expected path; once the shock hits, they update decisions using the realized crisis path. The same calibrated shock profile is also reused for the late-crisis counterfactual, which shifts the timing of the financial shock while holding its shape fixed.