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The Impact of Governmental Venture Capital on Venture Capital Activity:

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An Empirical Analysis of the German
Venture Capital Ecosystem

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16.12.2024

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Abstract: This research paper examines the impact of governmental venture capital (GVC) policies on venture capital activity in Germany using staggered Difference-in-Differences (DiD) methodology. Findings reveal significant increases in deal numbers and exits particularly in early-adopting states, with benefits accruing gradually over time. However, regional disparities persist, with weaker effects in less-developed states.

Keywords: Venture Capital, Governmental Venture Capital, Entrepreneurial Finance

1. Introduction

Venture capital (VC) is a critical driver of innovation, economic growth, and competitiveness in knowledge-based economies and when you think of VC you inevitably picture Silicon Valley, London and Berlin. This is not arbitrarily, since these regions have become entrepreneurial hubs as well as the playground for some of the most successful venture capitalists. Such concentration is expressed in positive regional effects on innovation, entrepreneurship, venture capital volume, deal numbers, aggregate income and further economic indicators. Consequently, regulators have been assessing and implementing schemes to further foster these hubs but also to encourage other regions to develop in similar trajectory and jumpstart economic growth. For example, European Central Bank (ECB) president Christine Lagarde has advocated for encouraging the development of the European VC markets through greater involvement of public development banks on several occasions, stressing the importance of VC for innovation and growth. Furthermore, the paramount importance of evaluating the impact and effectiveness of such policies is highlighted recurringly (Christine Lagarde & European Central Bank, 2023, 2024; Garret Walker, 2020).

This is at the core, of following analysis. It aims to produce findings that could inform both academic theory and practical policymaking, by assessing the impact of policy interventions in Germany in the form of governmental venture capital (GVC) provided by federal development banks. By employing a staggered Difference-in-Differences (DiD) methodology as proposed by

(Callaway & Sant'Anna, 2021), the study evaluates the dynamic and heterogeneous effects of GVC policies on venture capital activity, adding a more nuanced and comprehensive view to existing literature on the impact of GVC. The analysis reveals that GVC initiatives significantly increase deal and exit activity particularly in early-adopting states like Berlin or North Rhine-Westphalia and demonstrate a compounding effect over time. However, the findings also highlight persistent regional disparities, with economically weaker states showing more modest gains, suggesting structural barriers that limit policy effectiveness.

While the results affirm the critical role of GVC in addressing funding gaps and catalyzing ecosystem growth, they underscore the need for complementary measures such as infrastructure improvements and tailored support programs.

2. An overview of basic concepts and frameworks

This section examines the foundational concepts of venture capital and its role in driving innovation, entrepreneurship, and economic growth. It explores the theoretical basis for governmental intervention, focusing on market failures and funding gaps that hinder high-risk ventures. The discussion also highlights the structure and objectives of governmental venture capital programs and situates these within the broader European and German VC ecosystems.

2.1 Venture capital, funding innovation and economic growth

Venture capital (VC) is a form of private equity that provides financial support to early-stage, high-growth companies in exchange for equity stakes. The VC firms act as financial intermediaries, collecting funds from investors and allocating the funds to portfolio companies (PortCos) with the aim of growing these PortCos and selling the acquired stakes at a multiple in pre-determined cycles in order to return the multiplied funds to investors. VC is employed at early stages of start-ups at which the ventures have negative cash-flows and often an innovative but unproven product, service, and/or business model. Consequently, due to the associated uncertainty and high risk levels, traditional equity or debt financing is not available to founders. Through this early-stage financing and assumption of high risk it has been argued recurringly that VC firms play a critical role in fostering innovation, entrepreneurship and economic growth.

For one, innovation measured in numbers of patents submitted can clearly be linked to venture capital (Popov et al., 2012.; Tykvová, 2018). While research outlines that this effect is due to selection biases of VC firms which tend to invest in more innovative start-ups that already have patents pending/submitted or that produce products that are more likely to be patented, it also shows that VC-backed firms are better in commercializing protected intellectual property (Engel & Keilbach, 2007; Kortum & Lerner, 2000). It therefore can be deducted that, in terms of patents, VC does not increase innovation, but that venture capital enables the proliferation of innovation through commercialization.

On firm level, VC-backed companies also tend to have more employees, stronger growth across sales and cash-flow metrics (Engel & Keilbach, 2007; Keuschnigg, 2004; Samila & Sorenson, 2011). The positive impact of venture capital is argued to be derived from the rigorous selection process in start-up funding but also from the supplementary strategic guidance, business expertise, and access to industry networks that VC firms provide. This combination of financial and non-financial support is postulated to be the value-added that help VC-backed startups scale more rapidly and succeed in competitive markets (Bertoni, 2019; Engel & Keilbach, 2007).

These positive externalities affect not only the individual funded start-ups but also the wider economy e.g. in terms of firm starts, employment and aggregate income (Keuschnigg, 2004; Samila & Sorenson, 2011). For one, the sole availability of VC and VC-backed firms is correlated with further firm starts, beyond those financed, as it is postulated that the demonstration effect encourages entrepreneurs to start ventures (Keuschnigg, 2004). In addition, a self-reinforcing effect takes place when spin-offs are created by former startup employees turned founders. Macroeconomically, (Wasmer & Weil, 2002) showed in a study across 17 OECD countries that VC as share of GNP is inversely correlated with local unemployment rate both in short and long-term. This parallels, with further research that closely links the development of entrepreneurial clusters to decreased local unemployment rates (Glaeser et al., 2015).

2.2 Market failure theory and motivation for policy intervention

Market failure theory provides a foundational perspective for understanding the rationale behind governmental intervention in venture capital markets, especially within the context of stimulating economic growth and enhancing innovation competitiveness (Martin & Scott, 2000). Market failures occur when private markets fail to allocate resources in socially beneficial ventures due to lower financial return at their determined risk levels (Hall, 2002). Public intervention is thus considered essential for fostering growth in innovation-driven industries where private markets alone may not allocate sufficient resources (Bai et al., 2021; Hall, 2002). Government intervention under market failure theory is driven by the need to account for positive externalities and social benefits that are often disregarded in private investment decisions. In a practical example, a venture that has expected positive financial returns may not receive funding due to the availability of more lucrative investments. However, governmental agents may include other desired returns such as stimulation of employment, innovation or knowledge-spillovers in their assessment. As a result, the investment would be lucrative from a governmental perspective and with additional incentives could become financially viable for private investors as well.

Furthermore, venture capital investments often exhibit a strong local bias, where investors prioritize geographically proximate startups (Chen et al., 2010). This bias concludes in uneven distribution of VC funding, favoring established entrepreneurial hubs such as London, Berlin or Silicon Valley and potentially limits the development of nascent ecosystems, which is seen by some legislators as call to action. This phenomenon is attributed to the need for active monitoring, trust-building, and value-added support, which are facilitated by physical proximity (Chen et al., 2010; Sorenson & Stuart, 2001). Local bias is further reinforced by information asymmetries that make it challenging to assess distant investment opportunities. Research highlights that proximity reduces transaction costs and fosters a deeper understanding of regional markets and networks, enhancing the likelihood of investment success (Chen et al., 2010). Despite advancements in communication technologies, the local bias persists, particularly in early-stage investments, where uncertainty is high, and hands-on involvement is critical (Gompers & Lerner, 2001).

A further key motivator for governmental policies in VC is the previously outlined impact of VC on the direct success of funded firms and the wider economy. Young innovative firms are seen as essential for economic dynamism but often struggle to secure funding due to the high uncertainty and lack of collateral, causing private investors to hesitate despite potentially significant economic benefits (Martin & Scott, 2000). Increasing innovation, entrepreneurship, employment and income are all underlying motivators of governmental intervention in venture capital markets (Brander et al., 2015; Lerner, 2002). Brander et al., (2015), further outline in their research why governments may design policies targeting the financial intermediaries, instead of only focusing on directly incentivizing R&D, innovation and entrepreneurship. They highlight the importance of VC's in lowering informational asymmetries and selecting the more promising ventures whilst elevating the success rates of funded start-ups with strategic support. Incentivizing venture capital markets is therefore seen as valuable complement to other economic policies.

By addressing private funding gaps and enhancing the attractiveness of venture capital investments, governments can play a pivotal role in fostering a robust venture capital ecosystem whilst subsequently stimulating related economic indicators further downstream.

2.3 Governmental policies and governmental venture capital

As outlined, governmental policies are seen as essential in addressing funding gaps for early-stage, high-risk ventures, particularly in regions or sectors that lack private investment. These policies aim to bridge geographic and sectoral disparities in venture funding and encouraged intentional capital flows guided not solely by direct financial motives (Lerner, 2002). Broader governmental approaches include tax incentives on capital gains or management fees, supportive regulatory framework e.g. consistent insolvency laws or streamlined requirements for the allocation of risk capital and more. These foundational policies set the stage for localized approaches that can include loan guarantees, direct investments, co-investment schemes, and fund-of-fund models (Brander et al., 2015; Lerner, 2002). This research paper focuses on the latter. While there are differing definitions available for governmental venture capital (Colombo et al., 2016), this research paper will consider a narrower approach and will classify direct public funds, hybrid private-public funds, and fund of fund models as GVC.

Structurally, all GVC interventions frequently rely on public-private partnerships, where government resources are combined with those of the private sector. This can express itself in joint equity investments with private investors often mandated through matching-funds requirements, funding of private VCs as limited partners or opening up governmental VCs to private LPs (Bai et al., 2021). These co-investment approach leverages both the government's commitment to socially desired returns and private investors' drive for financial outcomes, enhancing GVC's potential as a catalyst that crowds in private capital rather than crowding it out (Guerini & Quas, 2016). As Colombo et al. (2016) note, GVC aims to strategically support national interests, such as technological advancement and sustainability, creating a resilient venture ecosystem that aligns with broader economic policies. Through well-structured interventions, GVC has the potential to effectively drive regional development, strengthen local industries, and encourage entrepreneurial activity aligned with societal goals, establishing a more inclusive and geographically diverse venture capital landscape.

2.4 The European and German venture capital ecosystem

The European venture capital ecosystem has consistently lagged behind the United States in terms of scale, accessibility, and maturity. In 2022, European VC investments amounted to €77 billion, representing 0.33% of Europe's GDP, significantly lower than the €188 billion, 0.78% of USA's GDP, invested in the U.S. (Ahrens-Gruber et al., 2023). While European early-stage investments are somewhat competitive, the disparity becomes stark in later-stage funding. On average, U.S. startups secure €13.7 million in late-stage investments, compared to just €5.8 million for their European counterparts (Startup Insider, 2024). This imbalance limits the ability of European firms to scale globally and compete effectively.

Fragmented regulatory frameworks, varying tax policies, and cultural risk aversion exacerbate the gap. Moreover, Europe lacks the strong institutional investor presence—such as pension funds—

that significantly contribute to the U.S. VC market. The smaller average deal size in Europe reflects these structural limitations, despite the continent's rich innovation landscape (Köppl-Turyna et al., 2021).

Germany, Europe's largest economy, faces similar challenges. VC investments in Germany in 2022 represented just 0.25% of GDP, compared to 0.78% in the U.S.(Ahrens-Gruber et al., 2023; Startup Insider, 2024). While early-stage investments are relatively robust, growth-stage funding falls substantially short, leaving many promising startups underfunded at critical expansion phases (Ahrens-Gruber et al., 2023). Several factors contribute to this gap. Structural inefficiencies, including complex regulatory environments and inconsistent taxation policies, hinder VC activity. Additionally, Germany's late-stage funding challenges mirror those of Europe, where investors are often reluctant to commit the significant capital required for scaling ventures (Honold et al., 2023).

Recognizing these challenges, European and German policymakers have introduced targeted measures to boost VC activity. At the EU level, the European Investment Fund (EIF) and the Juncker Plan are pivotal in addressing financing gaps and fostering cross-border investments. These initiatives aim to reduce administrative barriers and encourage institutional participation (Köppl-Turyna et al., 2021).

Germany has implemented its own interventions, such as the High-Tech Gründerfonds (HTGF), a hybrid public-private fund that bridges early-stage financing gaps, and programs like the "Zukunftsfinanzierungsgesetz", "financing the future law" in English, that focus on fostering private-public partnerships and providing tax incentives to attract private capital (Deutscher Bundestag, n.d., HTGF, n.d.). Additionally, to national policies, federal co-investment schemes, such as those implemented in Bavaria (Bayern Kapital) and Berlin (IBB Ventures), aim to stimulate regional VC activity by co-investing locally with private investors (Bayern Kapital, n.d., IBB Ventures n.d., Masiak et al., 2020). The latter will be the main focus of the following statistical analysis. The federal GVC schemes are of particular interest, since they were implemented independently and in a staggered approach, allowing for statistical Difference-in-Difference analysis. To their largest extent these funds comprise of funding form the European Investment Fund (EIF), national innovation schemes established by the German government as well as the individual federal governments. Furthermore, these federal governmental venture capital (FGVC) setups are aimed to encourage regional innovation, entrepreneurship and venture capital, by often having a strict investment policy of investing only in the corresponding state. This allows for greater quality of regression results, since spillover effects are limited. Furthermore, a majority of analyzed FGVC require as investment criteria the presence of private co-investors with the few FGVC exception stating their preference of having private participation in investments.

3. Review of prior research and hypothesis development

The interaction between governmental venture capital (GVC) and private venture capital (PVC) has been a critical area of research in the field of entrepreneurial finance. GVC is often utilized as a policy tool to address market inefficiencies and promote innovation-driven startup ecosystems, particularly in regions where private capital might be insufficient (Grilli & Murtinu, 2014)

In Germany, the federal and regional governments have adopted various GVC interventions to catalyze the venture capital ecosystem, with regions like Berlin (Berlin) and Munich (Bavaria) standing out due to their vibrant startup landscapes. The following sections deliberates on the existing literature regarding GVC and its impact on private venture capital markets as well as funded companies.

3.1 Impact of GVC on innovation, firm-start and firm performance

Governmental venture capital has been examined for its impact on innovation, firm creation, and firm performance, particularly in the US but also Europe and Germany. Studies generally highlight GVC's ability to address funding gaps for early-stage startups in high-risk industries, but findings regarding its broader effectiveness remain mixed. For instance, (Brander et al., 2015), conducted a cross-country analysis and found that while GVC fosters firm creation by bridging gaps in private sector financing, its impact on innovation is often contingent on the structure of the GVC program. In Germany, research by (Masiak et al., 2020) utilized regional data from 402 districts to analyze the geographic determinants of GVC investments. Their findings revealed that while GVC effectively increases firm starts in underfunded regions, its influence on firm performance, such as revenue growth and long-term survival, is less pronounced compared to private venture capital (PVC). Moreover, evidence from (Colombo et al., 2016) suggests that GVC's influence on innovation tends to materialize through co-investment schemes with private investors, which mitigate the risk of crowding out PVC. However, in regions with lower entrepreneurial activity, such as parts of Eastern Germany, GVC alone often fails to stimulate sustained innovation or firm growth (Guerini & Quas, 2016). Methodologically, these studies frequently employ regression analysis, Difference-in-Differences (DiD), or propensity score matching to isolate the effects of GVC from confounding factors. Yet, criticisms arise due to potential biases in sample selection, particularly the emphasis on funded firms over unfunded ones, which limits the generalizability of findings (Popov et al., 2012). Research that allows for dynamic heterogeneous effects, such as staggered DiD analysis by (Callaway & Sant'Anna, 2021), have not yet been employed in this context and would lend a more nuanced and comprehensive view.

In Germany, while initiatives such as the BayernKapital or High-Tech Gründerfonds (HTGF) have been lauded for their role in spurring innovation-driven startups, critiques persist regarding their scalability and the uneven distribution of GVC benefits across regions. Thus, while GVC can complement private capital in fostering firm starts and initial innovation, its long-term contributions to firm performance remain a topic of ongoing debate. Therefore, this research will not only analyze the impact of GVC on VC deal numbers but also on exits as proxy for successful VC investments.

3.2 Impact of GVC on PVC - crowding-in and crowding-out

Prior research suggests mixed outcomes regarding the impact of GVC on PVC activity. (Lerner, 1999) posits that GVC may crowd-in private investors by mitigating the risk of early-stage investments, thus encouraging PVC activity. However, more recent studies by (Bertoni, 2019) highlight the potential crowding-out effect, wherein the availability of public capital could diminish the incentive for private investors to engage in certain regions or sectors. Additionally, regional disparities play a significant role in the allocation of venture capital (Bertoni et al., 2013; Chen et al., 2010; Masiak et al., 2020). With government interventions being more pronounced in economically weaker regions, this raises the question of the differential impact of GVC on regional VC activity.

Building on this literature, this empirical analysis aims to investigate whether increased governmental venture capital directly influences, venture capital activity in Germany. By analyzing the regional variations in adoption of FGVC interventions and the subsequent changes in VC deal numbers the following hypothesis will be tested:

H1: *The inception of federal governmental venture capital schemes has a direct positive effect on overall venture capital activity in terms of deal numbers.*

H2: *The inception of federal governmental venture capital schemes has a direct positive effect on overall venture capital activity in terms of VC exit numbers (Buyout, M&A, IPO).*

H3: *The inception of federal governmental venture capital schemes has a direct positive effect on overall venture capital activity in terms of VC exit numbers (IPO).*

H4: *The inception of federal governmental venture capital schemes has a direct positive effect on overall venture capital activity in terms of deal volume.*

To assess venture capital activity, deal numbers and deal volume are commonly utilized due to their strong explanatory power and ease of interpretation. For the context of this research, these metrics are an imperfect but appropriate choice. This is because the federal GVC programs under study typically have strict co-investment policies, often partnering with private investors on a pari-passu basis. As a result, governmental participation inherently overlaps with private participation. Exits are also a meaningful metric to evaluate the success of financed ventures, however, their interpretation requires caution. To fully assess the success of exits, detailed data on entry and exit valuations for each deal would be necessary. Unfortunately, such valuation data is not readily publicly accessible for private equity investments. Consequently, IPOs are analyzed separately, as they are generally regarded as successful exits that create or realize value for existing investors. This approach provides a clearer perspective on the overall effectiveness of GVC policies in fostering value-generating activities.

4. Research methodology

Traditional Difference-in-Differences (DiD) models, which compare treated and untreated groups across a single intervention timeline, are insufficient for this analysis since German states implemented GVC policies at staggered intervals between 1997 and 2024. For example, while Baden-Württemberg, Bavaria, Mecklenburg-Western Pomerania and Saarland launched their first federal GVC funds/vintages before the year 2000, Hamburg launched its federal VC fund in 2012 and Schleswig-Holstein in 2018 (*Figure 1)*. This heterogeneity in policy timing introduces complexity that cannot be effectively captured using conventional methods. Therefore, this research paper will utilize a staggered DiD analysis with multiple time periods as proposed by (Callaway & Sant'Anna, 2021).

4.1 Model setup and assumptions

The staggered DiD model proposed by (Callaway & Sant'Anna, 2021) provides a more robust framework for this analysis. Unlike traditional approaches, which may yield biased estimates in the presence of varying treatment effects over time, this model accounts for heterogeneity in both the timing and impact of treatments. It enables the estimation of average treatment effects (ATT) for each cohort, thereby capturing the dynamics of policy implementation more accurately. This is particularly suited to examining how federal GVC policies influence outcomes such as the number of deals closed, deal volumes and number of VC exits over time and across multiple states. Furthermore, instead of comparing the treatment group with a "never-treated" comparison group, the staggered DiD allows comparison with a "not-yet-treated" comparison groups for the specific time periods. Callawy & Sant'Anna (2021) define several assumptions under which their model is developed (1) Irreversibility of Treatment, (2) Random Sampling, (3) Limited Treatment

Anticipation, (4) Conditional Parallel Trends Based on a "Never-Treated" Group or (5) Conditional Parallel Trends Based on "Not-Yet-Treated" Groups, (6) Overlap.

In context of this research, (1) assumes that once the GVC policies are implemented in the respective states, the policies will remain implemented throughout the observation period. This assumption is valid for all analyzed federal GVC policies, as these initiatives have maintained continuous operations. (2) Regards the independence and randomness of data chosen for analysis across units, i.e. states, and is supported by the evaluation of panel data across all 16 states accounting for state specific factors through covariates such as GDP or Population. (3) Is inherently linked with (4) or (5), inferring that venture capitalists, entrepreneurs and innovators did not anticipate the implementation of GVC in their state or at least did not change their behavior gravely in an observable manner. In the context of following research this is a valid assumption, further relativized through the use of covariates and the stringent test of parallel pre-treatment trends. Since all 16 states eventually implemented federal GVC no "never-treated" group exists, therefore (5) applies to this research. (5) Assumes conditional parallel trends based on "not-yet-treated" groups, inferring that without implementation of federal GVC programs the observed states would have followed similar trajectory in terms of the inspected outcome variables. This assumption is crucial and will be critically tested in 5.2. (6) Assumes the absence of cross-state spillovers, which is coherent with federal GVC's relatively strict guidelines of only investing in the corresponding states.

4.2 Model implications

Applying the staggered DiD model to this dataset offers insights into the temporal and spatial dynamics of federal GVC policies. By leveraging the variation in treatment timing, the model provides a detailed understanding of how policy impacts evolve over time. This is especially relevant for policies regarding venture capital, where the effects on outcomes such as deal numbers or deal volume may not be immediate but could materialize gradually as entrepreneurial ecosystems adjust to the availability of additional funding sources.

The model also accommodates heterogeneity in treatment effects across states. This is crucial given the variation in baseline characteristics, such as pre-existing entrepreneurial ecosystems, which may influence the effectiveness of federal GVC policies. For instance, the impact of Saxony's policy could differ significantly from that of Hamburg due to differences in their economic environments and innovation potential. By estimating treatment effects for each cohort, the model reveals these state-specific dynamics and provides a richer understanding of policy effectiveness.

Incorporating covariates such as number of firm starts and patents enhances the model's robustness by controlling for differences in baseline characteristics and pre-existing trends in entrepreneurship and innovation. This adjustment supports isolation of the true causal impact of GVC policies on venture capital activity. Moreover, while the primary analysis focuses on deal numbers, the model's flexibility allows it to be extended to secondary outcomes such as exit numbers and IPO numbers. This dual application ensures that the analysis captures both direct effects on venture capital activity and broader impacts on economic indicators of innovation and growth.

4.3 Dataset

The following analysis is based on a panel dataset covering 16 German states from 2000 to 2023, specifically adapted to evaluate the impact of federal governmental venture capital policies on venture capital activity, entrepreneurship, and innovation. The dataset combines multiple sources, including Pitchbook, the German Federal Statistical Office (Statistisches Bundesamt), the German Patent and Trade Mark Office DPMA, and federal GVC fund websites, ensuring comprehensive coverage of relevant variables.

Pitchbook is the primary source for venture capital deal data, including the number of deals, deal values, deal dates, and states. Manual cleaning was required to ensure consistency and accuracy. This involved reconciling discrepancies in city, postal code, and state data and imputing missing states where possible. Approximately 1,026 deals were excluded due to missing state information, resulting in a final sample of 15,576 deals across all 16 states from 2000 to 2023. While the dataset provides adequate coverage of deal numbers, the number of observations stating the respective deal values is significantly smaller, with only 8,185 observations available. Due to this limitation, the further analysis will only include deal volume or deal value in the limited scope of descriptive analysis. An additional dataset from Pitchbook consisting of 1,448 observations was employed to showcase VC-Exits. VC-Exits includes buyouts, merger and acquisitions as well as IPOs of previously VC-backed firms. Deal values of exits were disregarded, due to limited availability and questionable accuracy. An overview of outcome variables can be seen in *Figure 2*.

Data on GDP and Population were sourced from the Statistisches Bundesamt (German Federal Statistical Office), providing a consistent and reliable measure of state-level economic conditions. Patents data were obtained from the DPMA (German Patent and Trade Mark Office), serving as an indicator of innovation. Data on firm starts were also sourced from the Statistisches Bundesamt, acting as proxy for entrepreneurship. However, state-level data for firm starts for the year 2000 were unavailable, and only national-level figures were accessible for that period. This limitation is addressed by excluding firm starts data for 2000 from the analysis while maintaining it as a key variable for subsequent years.

Data on federal GVC funds, including implementation dates, fund sizes, and associated deals, were initially sourced from Pitchbook and cross-referenced with the websites of individual federal GVC funds for accuracy. This step ensured alignment between the incorporation dates and the associated venture capital activities. Additional information on federal VC funds was supplemented form further resources to fill gaps and verify missing data, further enhancing the reliability of the dataset. The FGVC funds were screened individually in order to assess differences in policy design. While all of the chosen funds have investment criteria stating that the funded startup must have their headquarters in corresponding states, only a majority have strict co-investment rules requiring the participation of private investors in financing VC deals. While such differences could potentially distort the interpretation of outcomes, it is reasonable to assume that most deals were still conducted in tandem with private investors as VC deals are rarely conducted by a single investor.

4.4 Variables

The primary variables include the annually aggregated *DealCount*, *ExitCount*, *IPOCount*, and *DealVolume* which represent the number of deals, number of exits, number of exits in form of IPOs and financial dimensions of venture capital activity for each state and year specific combination. *CompanyState* and *DealYear* specify the state and year for corresponding primary variables. Economic and innovation metrics, such as *GDP*, *Population*, *FirmStarts* and *Patents* are included to account for regional economic and entrepreneurial characteristics. Importantly, the variable *PostPolicy* distinguishes observations before and after the implementation of federal governmental venture capital funds (*Figure 2)*.

4.5 Measuring the impact of governmental venture capital on venture capital activity

The empirical analysis utilizes the staggered Difference-in-Differences (DiD) framework proposed by Callaway and Sant'Anna (2021). This methodology allows for the estimation of heterogeneous treatment effects across groups and over time, accommodating the staggered adoption of governmental venture capital policies across German states. The outcome variable Y_{it} , representing venture capital activity (e.g. *DealCount*, *ExitCount*, *IPOCount* or *DealVolume*) for state *i* at time *t*, is modelled as follows:

$$Y_{it} = \beta_0 + \sum_{g} \delta_{g,t} \cdot D_{g,it} + \gamma_1 \text{FirmStarts}_{it} + \gamma_2 \text{Patents}_{it} + \gamma_3 \text{GDP}_{it} + \gamma_4 \text{Population}_{it} + \gamma_5 \text{DealYear}_{t}$$

The intercept, β_0 captures the baseline level of venture capital activity across all states and time periods. The binary variable $D_{g,it}$ indicates whether a state *i* at time *t* belongs to treatment group *g*, representing states that implemented GVC policies in a given year. The treatment effect, $\delta_{g,t}$, represents the average treatment effect on the treated (ATT) for group *g* at time *t*. Further variable specifications can be found in *Figure 3.* State and year specific interaction terms have not been found to improve output quality and were consequently dropped to avoid unnecessary complexity.

5. Results

5.1 Descriptive analysis

The primary variables, *DealCount, ExitCount, IPOCount* and *DealVolume,* are examined across states to identify patterns and disparities in venture capital activity. *Figures 5-12* summarize the number of observation years, mean, standard deviation, min and max values for each variable across states, distinguishing between pre-policy (*PostPolicy* = 0) and post-policy (*PostPolicy* = 1) periods. Across all states a clear variation in VC activity can be observed. States such as Berlin and North Rhine-Westphalia exhibit significantly higher VC activity expressed in higher average post-policy *DealCount*, *ExitCount*, *IPOCount* and *DealVolume*. Berlin averages 270.55 deals, 22.6 exits, 0.75 IPOs, and €116.97M in deal volume per year and North Rhine-Westphalia averaging 83.25 deals, 8.85 exits, 0.35 IPOs, and €696.78M in deal volume per year. In contrast, less prominent states, such as Saxony-Anhalt and Rhineland-Palatinate, show substantially lower VC activity even after policy implementation, with mean post-policy activity of 6.52 deals, 0.94 exits, 0.58 IPOs, and €0M in deal volume per year and 15 deals, 1.2 exits, 0.2 IPO, and €1.35M in deal volume per year respectively.

In summary, the descriptive analysis highlights an increase in venture capital activity post-policy implementation, particularly in economically robust states like Berlin and Hamburg. However, regional disparities persist, with economically weaker states lagging in both deal/exit activity and monetary value. These findings emphasize the importance of contextual factors in shaping the effectiveness of GVC policies and provide a foundation for the subsequent empirical analysis. Furthermore, the descriptive analysis has shown, as previously postulated, that the dataset regarding *DealValues* is incomplete. Therefore, *DealVolume* and *DealValue* will be considered cautiously in further analysis.

5.2 Parallel trends analysis

The validity of the Difference-in-Differences (DiD) methodology hinges on the parallel trends assumption, which states that, in the absence of treatment, the outcomes for treated and control groups would have followed similar trends over time. Initial analysis revealed violations of this assumption when pre-treatment trends were tested across all groups. Specifically, the pre-treatment test yielded a chi-squared statistic of chi2(22)=15677.11 with a $p<0.001$, strongly rejecting the null hypothesis of parallel trends (*Figure 29)*.

To address this, the groups were reorganized into cohorts based on the timing of GVC policy implementation and analyzed separately for each outcome variable. Pre-treatment parallel trends tests for these clustered cohorts showed no significant violations of the assumption (*Figures 13-22)*. For example, in the cohort comprising states with policy start years in 2004, 2011, 2012 and 2017, the pre-treatment test for *DealCount* yielded chi2(22) = 25.32, $p = 0.2818$, supporting the null hypothesis of parallel trends (*Figure 13)*. Similarly, for the cohort with policy start years in 2004, 2007, 2008, 2011, 2012, 2017, and 2018 for *IPOCount*, the test returned chi2(15) = 12.98, $p = 0.6036$ (*Figure 21)*.

The clustering of cohorts effectively mitigated the initial violations, ensuring the robustness of the parallel trends assumption for the respective outcome variables. These results validate the use of the staggered Difference-in-Differences approach in analyzing the dynamic and heterogeneous effects of governmental venture capital policies across German states.

5.3 Baseline Difference-in-Differences results

As discussed in the previous section, the groups were further clustered into cohorts in order to comply with parallel trends assumptions for further difference-in-difference analysis. The regression results, each precluded by parallel trends tests, are illustrated in *Figure 13-22*.

DealCount

The aggregated average treatment effect on the treated (ATT) for *DealCount* is 37.94 deals per year (p<0.001), indicating a highly significant positive effect of GVC policies on the number of venture capital deals across treated states. Group-specific effects reveal substantial heterogeneity.

For example, early adopters such as the 2004 group (incl. Berlin, Brandenburg, North Rhine-Westphalia) experienced an ATT of 48.54 deals per year (p<0.001), while later adopters such as the 2012 group (incl. Hamburg) showed a smaller but still significant ATT of 10.6 deals per year (p=0.001). Furthermore it must be highlighted, that for the 2011 group (incl. Thuringia) the ATT is negative at -8.2 and significant (p<0.001) (*Figure 13*).

In the second cohort, the aggregated ATT is significantly positive, however somewhat lower at 8.9 (p<0.001). The average treatment effects for group 2007 (incl. Hesse, Saxony-Anhalt) is estimated at 5.81 (p=0.041) while for group 2008 (incl. Saxony) it is estimated at 15.6 (p<0.001) (*Figure 15*).

Over time, the dynamic effects indicate a gradual increase in *DealCount* for both cohorts. For instance, in the first cohort during the first two years post-treatment, the ATT is modest at 3.0 deals (p=0.028), but it rises steadily to 31.3 deals by the tenth year (p=0.027) (*Figure 13*) while in the second cohort it rises from 3.7 (p=0.202) in year 1 to 25 (p=0.199) in year 10 (*Figure 15)*. Outliers such as Berlin, with an exceptionally high baseline of deals post-policy implementation, potentially influence the overall ATT. Similarly, the negative ATT of group 2011 showcases an extreme and warrants further analysis.

ExitCount

The aggregated ATT for *ExitCount* is 3.4 exits per year (p<0.000), demonstrating a significant increase in exit activity following GVC interventions. Early adopters again show stronger effects, with the 2004 group achieving an ATT of 4.6 exits (p<0.000), whereas later adopters like the 2007 and 2012 group report smaller and less consistent effects (*Figure 17)*. Over time, the treatment effect for *ExitCount* grows gradually but inconsistently. During the first three years post-treatment, the ATT is modest at 1.9 (p=0.084), 1.6 (p=0.192) and 2.7 (p=0.001) exits respectively, reaching a peak of 5.4 exits by the eighth year (*p*=0.014) and further accerlating to 14 (p=0.014) in year 10. However, it must be highlighted that increases are not fully consistent which can be seen clearly in graphical anlysis (*Figure 18*). Outliers such as Berlin contribute to significant regional variations, but sensitivity checks confirm the robustness of results across groups. The second cohort reports negative aggregated ATT at -0.83, however with no statistical significance (p=0.433) (*Figure 19)*.

IPOCount

The ATT for *IPOCount* is 0.59 increase in IPOs per year (p>0.000), which is smaller in magnitude and exhibits statistical significance (*Figure 21)*. Early adopters, such as the 2004 group, report a lower ATT of 0.51 IPOs (p<0.000), while group 2007 display effects that are larger and statistically significant. Due to limited observations of IPOs and limited data for more recent adopters such as groups 2011 and 2012 no p-values or confidence intervals are calculated, hindering interpretation of those coefficents. Dynamic effects show a slow build-up in IPO activity (*Figure 21, 22)*. The ATT increases to 0.4 IPOs per year by the eight year post-treatment (p=0.066), though growth fluctuates.

To conclude, the baseline Difference-in-Differences results confirm significant positive effects of GVC policies on venture capital activity, particularly for *DealCount* and *ExitCount*, with dynamic treatment effects showing sustained growth over time. Regional outliers such as Berlin and North Rhine-Westphalia amplify aggregate results, underscoring the importance of adjusting for these influential cases in the robustness checks. Smaller and less consistent effects for *IPOCount* are measured, warranting caution in interpretation.

5.4 Robustness checks

To further strengthen the reliability of regression results a sensitivity test was conducted by excluding the state of Berlin which encompasses the city of Berlin, a significant outlier as Germany's governmental capital as well as it's hub for entrepreneurial activity.

DealCount

Excluding Berlin resulted in a notable reduction in the aggregated ATT for *DealCount* from 37.94 deals per year (p<0.001) to 10.16 deals per year (p=0.004), indicating that Berlin significantly amplifies the observed treatment effects. The confidence interval for the adjusted ATT changed, from [17.80, 58.08] in the full sample to [3.22, 17.09], reflecting remaining uncertainty in effect magnitude. Dynamic treatment effects for *DealCount* remained positive and significant over time but displayed reduced magnitudes, particularly in later periods. For example, the tenth-year post-treatment ATT decreased from 103.66 (p=0.125) to 22 (p=0.225) (*Figure 23).*

ExitCount

The exclusion of Berlin similarly reduced the ATT for *ExitCount* from 3.48 exits per year (p<0.000) to 1.83 exits per year (p=0.014). While the ATT remained statistically significant, the confidence interval shifted from [1.72, 5.24] in the full sample to [0.37, 3.30] in the adjusted analysis, indicating a more modest policy impact without Berlin. The dynamic effects also showed reduced magnitudes. For example, the eighth-year post-treatment ATT for *ExitCount* decreased from 5.4 exits (p=0.014) to 3.5 exits (p=0.082) (*Figure 25).*

IPOCount

For *IPOCount*, the exclusion of Berlin showed an increase in the ATT, which changed from 0.59 IPOs per year (p<0.000) to 0.733 IPOs per year (p=0.01). The adjusted ATT remained statistically significant, and the confidence interval widened slightly, from [0.33,0.86] to [0.31,1.15]. These results suggest that the policy implementation impacted Berlin in a less prominent or even negative manner, compared to the studied states (*Figure 27)*.

6. Discussion

6.1 Discussion of key results

This study highlights the significant and heterogeneous impact of governmental venture capital policies on venture capital activity across German states. The staggered Difference-in-Differences methodology reveals that GVC policies have a pronounced effect on deal counts, particularly in early-adopting states such as Berlin or North-Rhine Westphalia. The long-term benefits, evidenced by the sustained growth in deal activity, suggest that these policies have fostered regional entrepreneurial ecosystems, effectively supporting **H1**. This supports the theory of GVC, crowding-in private investors, when policy design emphasizes co-investments. Furthermore, the regression results show a positive significant effect of governmental venture capital on number of venture capital exits in terms of buyouts, M&As, and IPOs. Inference as to GVC's effectiveness of supporting successful ventures are possible yet would warrant more detailed analysis of the individual ventures financed by GVC. Subsequently, also a direct causal relationship is indicated in terms of the studied FGVC policies and numbers of IPOs. These results may however be of lower statistical value, due to limited observations. Therefore, it can be concluded that this research finds support for **H2** and **H3** as well. **H4** could not be confirmed or rejected due to incomplete data with low reliability and will have to be analyzed with different datasets. Furthermore, regional disparities in treatment effects - stronger in economically advanced states like Hamburg and North Rhine-Westphalia and weaker in smaller or economically disadvantaged states in the East -

underscore the contextual nature of GVC impacts. Similarly, significant outliers such as Thuringia (g2011), warrant further analysis to discern the true cause of their extreme ATT which could stem from a multitude of distinct factors including GVC policy design or overall state specific changes e.g. political nature. These findings complement existing literature emphasizing the role of pre-existing infrastructure and economic conditions in amplifying or limiting policy effectiveness.

Dynamic treatment effects further show that the benefits of GVC policies accumulate over time, peaking years after implementation. This gradual maturation aligns with theories on the compounding nature of venture capital ecosystems, where early-stage support eventually translates into broader ecosystem growth.

6.2 Contributions and implications for theory and practice

This research contributes to the literature on public policy interventions in entrepreneurial finance by providing empirical evidence on the heterogeneous and dynamic effects of GVC policies. It emphasizes the importance of staggered DiD analysis as a methodological advantage, allowing nuanced insights into policy effectiveness over time and across regions.

For practitioners, these findings highlight the need for region-specific policy designs. While GVC policies catalyze venture capital activity in advanced ecosystems (e.g. Berlin, NRW, Hamburg), their less pronounced success in less-developed regions (e.g. Hesse, Saxon-Anhalt) suggests that complementary interventions, such as infrastructure development or tailored support programs, are necessary to maximize impact. Furthermore, this research provides a nuanced mapping of the German venture capital ecosystem as well as FGVC programs and their distinct characteristics, aiding in the exploration of Europe's largest economy.

6.3 Limitations and future research

While offering valuable insights, this analysis, has several limitations that warrant further consideration. First, the reliance on Pitchbook **data** introduces potential biases, particularly in underrepresenting smaller deals and less-developed regions. Integrating alternative data sources could provide a more comprehensive view of venture capital activity across all states. Second, although the analysis adjusts for initial deviations from the **strict parallel trend assumption** by using cohorts that sufficiently satisfy the assumption residual concerns remain, due to lower numbers in comparable treatment groups. Incorporating more granular pre-treatment covariates might further enhance the validity of the findings. Another limitation lies in the **assumption of limited cross-state spillovers**. While this assumption aligns with the strict state-specific guidelines of federal GVC policies, regional interdependencies, such as cross-border investments, may still influence outcomes. Future research could explore these spillover effects through network-based analytical approaches. Additionally, this study does not fully account for **variability in policy design** and implementation across states. Differences in fund sizes, investment criteria, or operational structures could play a significant role in determining policy effectiveness and merit further investigation. Finally, while the findings provide critical insights into the German context, their **generalizability** to other countries with different venture capital ecosystems or policy landscapes remains uncertain. Comparative analyses across diverse national settings could offer a broader perspective. Future research could also delve into secondary outcomes, such as firm survival rates or long-term innovation metrics, to provide a more holistic understanding of the broader impacts of governmental venture capital initiatives.

7. Conclusion

This research demonstrates that the impact of governmental venture capital policies on venture capital activity is both significant and dynamic, with benefits accumulating over time as regional ecosystems mature. Dynamic treatment effects reveal that GVC policies catalyze further VC activity gradually and culminate in more exits, aligning with the compounding nature of venture capital investments and potentially suggesting beneficial investment decisions of GVC funds. The initial funding provided by these policies not only addresses immediate financial gaps but also fosters broader ecosystem growth in the long run. However, the persistence of regional disparities highlight the structural barriers faced by less-developed states, where GVC programs have had comparatively lower success. These findings suggest that while GVC policies are effective in stimulating venture capital activity, their impact could be amplified when complemented by targeted measures such as regulatory improvements, skill development, and localized entrepreneurial support.

From a policy perspective, this dual role of GVC programs—bridging funding gaps and catalyzing systemic growth—underscores the importance of a nuanced, context-specific approach. Policymakers should leverage these insights to design initiatives that not only enhance venture capital activity but also address the unique challenges of underperforming regions, maximizing the broader economic and social benefits of governmental venture capital investments.

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9. Appendix

9.1 Descriptive Figures

State	GVC Investore Name	First VC Fund Name	First VC Fund Vintage	Nr. of VC Funds	Investments	Active Portfolio	Investments in the last 12 months	Investments in the last 5 years
Baden-Württemberg	LBBW Venture Capital	LBBWVC	1998	-	77	23	6	20
Bavaria	Bayern Kapital	Technofonds Bayern	1998	7	353	112	33	122
Berlin	IBB Ventures	VC Fonds Berlin	2004	6	338	106	14	104
Brandenburg	Brandenburg Kapital	BC Venture	2004	8	160	48	10	48
Bremen	Bremer Aufbau Bank	Bremer VC Fund	2024	1	#N/A	#N/A	#N/A	#N/A
Hamburg	IFB Innovationsstarter	Innovationsstarter Fonds	2012	2	336	254	43	194
Hesse	Hessen Kapital	Hessen Kapital I	2007	3	28	19	1	18
Lower Saxony	NBank Capital	Nseed Fund	2017	1	92	74	8	56
Mecklenburg-Western Pomerania	GENIUS Venture Capital	Genius VC	1998	-	33	8	1	8
North Rhine-Westphalia	NRW.Bank	NRW.Bank Fonds Beteiligungs	2004	5	141	49	8	56
Rhineland-Palatinate	Investitions- und Strukturbank Rheinland-Pfalz	Rhineland Palatinate Innovation Fund	2019	3	38	20	1	12
Saarland	Saarländische Wagnisfinanzierungsgesellschaft	SWG	1997	-	53	24	1	8
Saxony	Technologiegründerfonds Sachsen	Technology Start-up Fund Saxony	2008	2	159	72	10	73
Saxony-Anhalt	IBG Beteiligungsgesellschaft Sachsen-Anhalt	IBG Venture Capital Fund I	2007	5	131	35	1	21
Schleswig-Holstein	MBG Schleswig-Holstein	VC-Fonds Schleswig-Holstein	2018	2	46	27	3	22
Thuringia	bmt beteiligungsmanagement thüringen gmbh	Thüringer Gründerfonds	2011	#N/A	#N/A	#N/A	#N/A	#N/A

Figure 1: Federal GVC Overview

Variable Name	Description	Type	Notes
CompanyState	State in which the company is located	String (str29)	Includes 16 German states.
DealCount	Number of deals in respective year and state	Numeric (int)	Ranges from 1 to 736; mean = 248.46.
DealVolume	Total value of deals in respective year and state	Numeric (double)	Ranges from 0 to 10614.09 million euros.
DealYear	Year of the deal	Numeric (int)	Ranges from 2000 to 2023.
ExitCount	Number of exits (Buyout, M&A, IPO) in respective year and state	Numeric (byte)	Ranges from 0 to 59; mean = 3.77.
FirmStarts	Number of firm startups in respective year and state	Numeric (long)	Missing values (80); ranges from 4194 to 201,935.
GDP	State-level GDP (in billions of euros)	Numeric (double)	Ranges from 23.07 to 839.08 billion euros.
IPOCount	Number of IPOs in respective year and state	Numeric (byte)	Ranges from 0 to 5; mean = 0.15.
Patents	Number of patents filed in respective year and state	Numeric (int)	Ranges from 89 to 15,835.
PolicyStartYear	Year the VC policy started in the state	Numeric (int)	Ranges from 1997 to 2024.
Population	State-level population (in millions)	Numeric (double)	Ranges from 0.651 to 18.19 million.
PostPolicy	Indicator for post-policy implementation (0/1)	Numeric (float)	Binary: 0 = pre-policy, 1 = post-policy.
Region	Indicator for State cluster i.e. West and East Germany (1/2)	Numeric (float)	Binary: 1 = West, 2 = East.
StateID	Numeric identifier for each state	Numeric (long)	Includes 16 German states.

Figure 2: Overview of Variables

Term	Description
Y_{it}	Number of deals (`DealCount`) in state i during year t.
β_0	Intercept term.
$\delta_{g,t}$	Group-time average treatment effect (ATT) for states first treated in year g at time t.
$D_{g,it}$	Indicator variable equal to 1 if state i is in group g at time t.
$\gamma_1 FirmStarts_{it}$	Effect of the number of firm starts in state i during year t.
$\gamma_2 Patents_{it}$	Effect of the number of patents filed in state i during year t.
$\gamma_3 GDP_{it}$	Effect of Gross Domestic Product (GDP) in state i during year t.
$\gamma_4 Population_{it}$	Effect of population size in state i during year t.
$\gamma_5 DealYear_t$	Overall time trend in deals.
$\sum_s \gamma_{6,s} CompanyState_i$	State fixed effects to control for unobserved heterogeneity across states.
$\sum_s \gamma_{7,s}(DealYear_t \times CompanyState_i)$	State-specific time trends modeled through interaction terms.
ε_{it}	Idiosyncratic error term.

Figure 3: Description of Formula

Cohort	CompanyState	DealCount	ExitCount	IPOCount	DealVolume	PolicyStartYear
		# Obs.	*# Obs.*	*# Obs.*	*# Obs.*	
<2000	Baden-Württemberg	1169	98	3	534	1998
	Bavaria	3221	294	16	1578	1998
	Mecklenburg-Western Pomerania	96	11	0	37	1998
	Saarland	81	40	0	30	1997
2004	Berlin	5436	452	15	2885	2004
	Brandenburg	373	37	1	174	2004
	North Rhine-Westphalia	1698	75	10	672	2004
2007	Hesse	726	6	3	318	2007
	Saxony-Anhalt	123	10	1	58	2007
2008	Saxony	583	17	1	266	2008
2011	Thuringia	129	17	1	49	2011
2012	Hamburg	1201	182	6	492	2012
2017	Lower Saxony	312	62	1	113	2017
2018	Schleswig-Holstein	185	15	0	79	2018
2019	Rhineland-Palatinate	146	16	2	69	2019
2024	Bremen	97	116	0	37	2024
	Total	**15576**	**1448**	**60**	**7391**	

Figure 4: Overview of VC deal activity distribution

Notes: Data on VC deals, volumes, and exits were sourced from Pitchbook, a trusted financial database with comprehensive coverage of global venture capital activity. Pitchbook data, while comprehensive, may underrepresent smaller deals and rely on self-reported information, which could introduce selection bias or incomplete coverage. For further information see https://pitchbook.com/research-process

Data on federal venture capital funds was sourced from pitchbook as well as the individual funds websites and further governmental sources. Due to varying transparency in regard to fund sizes, investments, investment criteria some mediating assumptions were drawn as discussed previously.

CompanyState = Baden-Württemberg PostPolicy = 0

CompanyState = Baden-Württemberg PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	24	48.70833	49.84191	3	169
ExitCount	24	4.083333	2.91796	0	10
IPOCount	24	0.125	0.337832	0	1
DealVolume	24	1493.25	2619.76	0	10614.09
FirmStarts	23	98020.91	9205.924	86040	116463
-------------	-------------	-------------	-------------	-------------	-------------
Patents	24	13954.92	984.9059	11610	15239
GDP	24	425.5713	89.08893	308.823	615.071
Population	24	10.79468	0.2332353	10.489	11.33926

CompanyState = Bavaria PostPolicy = 0

CompanyState = Bavaria PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	24	134.2083	124.8449	10	377
ExitCount	24	12.25	9.799068	0	37
IPOCount	24	0.6666667	1.129319	0	5
DealVolume	24	441.9275	652.9125	11.69	2480.68
FirmStarts	23	130623.6	14425.36	113311	158844
-------------	-------------	-------------	-------------	-------------	-------------
Patents	24	13761.46	1356.189	10549	15835
GDP	24	510.4724	119.8093	357.9	768.469
Population	24	12.66678	0.3409703	12.175	13.43506

Figure 5: Descriptive Analysis

CompanyState = Berlin PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	4	6.25	3.774917	3	10
ExitCount	4	0	0	0	0
IPOCount	4	0	0	0	0
DealVolume	4	20.85	15.74887	0	35.62
FirmStarts	3	34221	2995.027	31414	37374
-------------	-------------	-------------	-------------	-------------	-------------
Patents	4	1169.5	75.95832	1099	1242
GDP	4	85.83475	0.4784861	85.341	86.368
Population	4	3.3875	0.0036968	3.384	3.392

CompanyState = Berlin PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	20	270.55	235.7417	8	736
ExitCount	20	22.6	18.34293	1	59
IPOCount	20	0.75	1.019546	0	4
DealVolume	20	116.9785	188.5885	0	589.69
FirmStarts	20	44146.6	2518.477	40391	48716
-------------	-------------	-------------	-------------	-------------	-------------
Patents	20	805.9	169.4384	476	1030
GDP	20	125.437	32.29949	85.425	193.219
Population	20	3.501501	0.1377546	3.3	3.782202

CompanyState = Brandenburg PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	4	2	2	1	5
ExitCount	4	0.25	0.5	0	1
IPOCount	4	0	0	0	0
DealVolume	4	38.7025	47.54773	0	97.29
FirmStarts	3	21893.67	1917.953	20275	24012
-------------	-------------	-------------	-------------	-------------	-------------
Patents	4	396	12.19289	379	408
GDP	4	45.822	0.8395761	44.672	46.598
Population	4	2.59075	0.0105633	2.577	2.6

CompanyState = Brandenburg PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	20	18.25	13.47464	0	49
ExitCount	20	1.8	1.880649	0	7
IPOCount	20	0.05	0.2236068	0	1
DealVolume	20	65.4255	155.9077	0	656.9
FirmStarts	20	20358.55	3843.015	17049	30163
-------------	-------------	-------------	-------------	-------------	-------------
Patents	20	322.1	54.24011	195	428
GDP	20	64.971	13.70581	47.824	97.477
Population	20	2.507887	0.0470339	2.448	2.581667

Figure 6: Descriptive Analysis

CompanyState = Bremen — PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	24	4.041667	4.610755	0	15
ExitCount	24	0.4583333	0.72106	0	2
IPOCount	24	0	0	0	0
DealVolume	24	1.399583	6.85653	0	33.59
FirmStarts	23	5878.826	753.3004	4194	6912
Patents	24	149.125	24.70401	102	198
GDP	24	28.84517	4.560448	22.29	39.252
Population	24	0.66609	0.0101047	0.651	0.691703

CompanyState = Bremen — PostPolicy = 1

CompanyState = Hamburg — PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	12	10.33333	7.426407	1	25
ExitCount	12	1.916667	1.676486	0	5
IPOCount	12	0.1666667	0.3892495	0	1
DealVolume	12	78.85333	162.2357	0	561.68
FirmStarts	11	21725.27	2055.878	17694	24632
Patents	12	1056.917	150.1572	919	1427
GDP	12	87.74242	5.467867	77.837	94.664
Population	12	1.742417	0.0255751	1.706	1.78

CompanyState = Hamburg — PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	12	89.75	50.64336	28	190
ExitCount	12	7.75	2.598076	5	14
IPOCount	12	0.3333333	0.492366	0	1
DealVolume	12	40.12583	95.94511	0	289
FirmStarts	12	20236.67	1483.744	17935	22743
Patents	12	692.6667	180.1612	377	882
GDP	12	119.5523	17.4831	97.009	150.575
Population	12	1.813891	0.0574622	1.726	1.91016

Figure 7: Descriptive Analysis

CompanyState = Hesse — PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	7	3.142857	1.676163	1	6
ExitCount	7	1.714286	1.496026	0	4
IPOCount	7	0.1428571	0.3779645	0	1
DealVolume	7	36.96143	35.03884	0	92.3
FirmStarts	6	71110.17	8138.177	61113	79629
Patents	7	3977.857	485.2448	3248	4688
GDP	7	205.999	8.090442	193.586	218.077
Population	7	6.079	0.01253	6.056	6.092

CompanyState = Hesse — PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	17	41.41176	31.05652	6	88
ExitCount	17	3.705882	3.216456	1	13
IPOCount	17	0.1176471	0.3321056	0	1
DealVolume	17	21.07	25.03463	0	69.47
FirmStarts	17	67148.65	8203.932	56895	79775
Patents	17	1984.412	526.4875	1089	3013
GDP	17	266.9318	38.24847	219.381	351.139
Population	17	6.151604	0.1325941	5.979	6.420729

CompanyState = Lower Saxony — PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	17	5.117647	4.255619	0	14
ExitCount	17	1.294118	1.649421	0	6
IPOCount	17	0.0588235	0.2425356	0	1
DealVolume	17	36.84941	81.16779	0	251.93
FirmStarts	16	68999.13	7794.739	57247	84472
Patents	17	3049.647	294.8349	2610	3703
GDP	17	220.6079	30.47435	183.712	280.611
Population	17	7.911706	0.0815336	7.778	8

CompanyState = Lower Saxony — PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	7	32.14286	8.434623	23	46
ExitCount	7	2.571429	1.397276	0	4
IPOCount	7	0	0	0	0
DealVolume	7	8.834286	14.32054	0	34.47
FirmStarts	7	61367.71	3463.582	57609	65950
Patents	7	3258	412.0235	2792	3852
GDP	7	317.2437	26.12594	287.902	363.109
Population	7	7.979382	0.1414151	7.824	8.161981

Figure 8: Descriptive Analysis

CompanyState = Mecklenburg-Western Pommerania PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	24	4	4.343911	0	14
ExitCount	24	0.4166667	0.5835921	0	2
IPOCount	24	0	0	0	0
DealVolume	24	5.817083	28.49777	0	139.61
FirmStarts	23	12615.35	2937.646	9311	20407
-------------	-------------	-------------	-------------	-------------	-------------
Patents	24	166.125	39.66634	89	243
GDP	24	38.50396	8.44952	29.253	59.217
Population	24	1.653866	0.0654406	1.577	1.786

CompanyState = Mecklenburg-Western Pommerania PostPolicy = 0

CompanyState = North Rhine-Westphalia PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	4	8.25	4.5	6	15
ExitCount	4	1.25	1.5	0	3
IPOCount	4	0.75	1.5	0	3
DealVolume	4	365.52	509.2809	97.7	1129.31
FirmStarts	3	157782.7	11203.41	150943	170712
-------------	-------------	-------------	-------------	-------------	-------------
Patents	4	9573.75	628.1387	8975	10274
GDP	4	476.6735	8.438368	465.177	483.034
Population	4	18.032	0.0376829	17.989	18.071

CompanyState = North Rhine-Westphalia PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	20	83.25	65.89296	8	202
ExitCount	20	8.85	4.760307	3	17
IPOCount	20	0.35	0.8127277	0	3
DealVolume	20	696.781	1073.396	49.08	3785.14
FirmStarts	20	162423.8	18994.06	136892	201935
-------------	-------------	-------------	-------------	-------------	-------------
Patents	20	7117.55	928.5287	5293	8875
GDP	20	628.4483	98.54607	496.191	839.084
Population	20	17.84598	0.2131999	17.541	18.19042

Figure 9: Descriptive Analysis

CompanyState = Rhineland-Palatinate PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	19	3.736842	3.106304	0	11
ExitCount	19	0.5789474	0.606977	0	2
IPOCount	19	0.0526316	0.2294157	0	1
DealVolume	19	87.65632	131.0097	0	528.05
FirmStarts	18	38466.11	4327.261	31658	46550
-------------	-------------	-------------	-------------	-------------	-------------
Patents	19	1563.895	682.4199	911	2719
GDP	19	113.6153	16.3631	93.617	143.06
Population	19	4.029105	0.0257075	3.99	4.064

CompanyState = Rhineland-Palatinate PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	5	15	3.605551	10	20
ExitCount	5	1.2	0.83666	0	2
IPOCount	5	0.2	0.4472136	0	1
DealVolume	5	1.356	1.825508	0	4.44
FirmStarts	5	32533	1621.377	31325	34878
-------------	-------------	-------------	-------------	-------------	-------------
Patents	5	776.2	99.83837	605	856
GDP	5	159.9928	13.7616	144.431	174.249
Population	5	4.111067	0.0619315	4.017	4.174311

CompanyState = Saarland PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	24	3.375	3.145908	0	12
ExitCount	24	0.25	0.5316095	0	2
IPOCount	24	0	0	0	0
DealVolume	24	2.109167	10.33276	0	50.62
FirmStarts	23	7957.652	1083.389	6531	10209
-------------	-------------	-------------	-------------	-------------	-------------
Patents	24	258.125	77.22824	98	368
GDP	24	31.89954	4.300336	25.343	41.348
Population	24	1.01681	0.0341832	0.972	1.071

CompanyState = Saarland PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max

Figure 10: Descriptive Analysis

CompanyState = Saxony PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	8	4.375	2.924649	1	9
ExitCount	8	0.625	0.9161254	0	2
IPOCount	8	0	0	0	0
DealVolume	8	104.1787	138.6952	0	328.51
FirmStarts	7	41841.29	4673.127	35681	49171
-------------	-------------	-------------	-------------	-------------	-------------
Patents	8	892.625	61.933	814	1000
GDP	8	83.374	5.529107	75.609	92.657
Population	8	4.333375	0.0742677	4.235	4.448

CompanyState = Saxony PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	16	34.25	18.64225	10	70
ExitCount	16	3.5625	2.25	0	7
IPOCount	16	0.0625	0.25	0	1
DealVolume	16	34.01313	58.32806	0	185.64
FirmStarts	16	30578.25	4936.494	25728	39526
-------------	-------------	-------------	-------------	-------------	-------------
Patents	16	849	230.0171	544	1224
GDP	16	116.7535	19.38468	90.848	155.982
Population	16	4.073785	0.0588235	4.002	4.205

CompanyState = Saxony-Anhalt PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	7	1.714286	1.253566	0	3
ExitCount	7	0	0	0	0
IPOCount	7	0	0	0	0
DealVolume	7	45.73286	98.20604	0	263.18
FirmStarts	6	20440.83	2665.904	17258	25071
-------------	-------------	-------------	-------------	-------------	-------------
Patents	7	407.1429	50.31046	345	492
GDP	7	44.82443	1.736914	42.47	47.699
Population	7	2.544857	0.0659784	2.456	2.641

CompanyState = Saxony-Anhalt PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	17	6.529412	3.104788	3	12
ExitCount	17	0.9411765	0.9663455	0	3
IPOCount	17	0.0588235	0.2425356	0	1
DealVolume	17	0	0	0	0
FirmStarts	17	12972.18	2599.816	9845	17868
-------------	-------------	-------------	-------------	-------------	-------------
Patents	17	232.9412	75.61619	122	367
GDP	17	59.20141	8.646483	48.316	78.38
Population	17	2.252002	0.0856414	2.159	2.428

Figure 11: Descriptive Analysis

CompanyState = Schleswig-Holstein PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	18	2.888889	2.632129	0	8
ExitCount	18	0.6666667	0.8401681	0	3
IPOCount	18	0	0	0	0
DealVolume	18	50.46167	171.8227	0	737.23
FirmStarts	17	29716.12	3070.862	25561	36359
-------------	-------------	-------------	-------------	-------------	-------------
Patents	18	558.8889	81.90661	436	679
GDP	18	74.12411	8.590659	63.74	92.62
Population	18	2.822556	0.0205805	2.781	2.866

CompanyState = Schleswig-Holstein PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	6	22.16667	9.217737	11	38
ExitCount	6	0.5	0.83666	0	2
IPOCount	6	0	0	0	0
DealVolume	6	55.58167	50.76826	0.01	141.22
FirmStarts	6	25899.83	892.1194	24752	27060
-------------	-------------	-------------	-------------	-------------	-------------
Patents	6	447.6667	37.372	383	481
GDP	6	105.3817	9.132729	95.008	118.68
Population	6	2.907307	0.0516084	2.841	2.965691

CompanyState = Thuringia PostPolicy = 0

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	11	2.545455	2.733629	0	7
ExitCount	11	0.5454545	0.6875517	0	2
IPOCount	11	0	0	0	0
DealVolume	11	79.96455	161.7502	0	507.32
FirmStarts	10	19977.7	2454.041	17158	25276
-------------	-------------	-------------	-------------	-------------	-------------
Patents	11	704.1818	86.45903	592	849
GDP	11	43.62036	2.788993	39.525	47.829
Population	11	2.343455	0.069206	2.241	2.445

CompanyState = Thuringia PostPolicy = 1

Variable	Obs	Mean	Std.dev	Min	Max
DealCount	13	7.769231	3.811252	3	14
ExitCount	13	0.8461538	0.8006408	0	2
IPOCount	13	0.0769231	0.2773501	0	1
DealVolume	13	0	0	0	0
FirmStarts	13	12207.54	1556.094	10481	15695
-------------	-------------	-------------	-------------	-------------	-------------
Patents	13	544.3846	40.31447	471	607
GDP	13	60.90169	7.429932	50.625	75.909
Population	13	2.138868	0.0292881	2.102	2.187

Figure 12: Descriptive Analysis

9.2 Regression output

Note: the regression outputs show the aggregated results for each cohort. The cohort groups are specified in the description of each *Figure*. To obtain regression results for a staggered DiD regression stata command `csdid DealCount, time(DealYear) id(CompanyState) gvar(PolicyStartYear) covariates(FirmStarts Patents GDP Population)` was employed, after previously specifying the study objects i.e. groups. To retrieve aggregate results command `estat all` was utilized. Precluding each regression a test was conducted (`estat pretrend`) to evaluate the pretreatment parallel trends. It tests the null hypothesis that there are no significant differences between the treated and the control group for specified timelines. If p>0.05 we can confidently reject the null hypothesis and determine the parallel pretreatment trend as confirmed. (For further reference see Callaway and Sant'Anna, 2021 as well as Rios-Avila, et al. Stata Conference, 2021)

Figure 13-28, show the aggregated ATT for each cohort as well as the ATTs for each studied group (with enough observations and existing control groups) and the dynamic effects as per calendar year and as per time to treatment. While the aggregates are mostly statistically significant, ATT for each time period are less confident due to limited observations. This can also be seen in the graphs and corresponding confidence intervals. They nonetheless have explanatory value.

Figure 29-31 showcase the staggered DiD regression with all groups. However as highlighted previously the parallel pretreatment trend assumption cannot be upheld, therefore results were not discussed in detail.

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(22) = 25.3242
p-value = 0.2818
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
ATT	37.94	10.2777	3.69	0.000	17.79608	58.08392

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
GAverage	29.60974	7.226383	4.10	0.000	15.44629	43.77319
G2004	48.53846	11.96834	4.06	0.000	25.08095	71.99597
G2011	-8.166667	1.711548	-4.77	0.000	-11.52124	-4.812093
G2012	10.6	3.12602	3.39	0.001	4.473114	16.72689

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
CAverage	32.53846	8.675453	3.75	0.000	15.53489	49.54204
T2004	3.333333	4.260064	0.78	0.434	-5.016239	11.68291
T2005	2.666667	2.403701	1.11	0.267	-2.0445	7.377834
T2006	6.666667	4.38009	1.52	0.128	-1.918151	15.25148
T2007	12.66667	8.164966	1.55	0.121	-3.336372	28.66971
T2008	18.33333	9.08397	2.02	0.044	.5290785	36.13759
T2009	22	11.12555	1.98	0.048	.1943302	43.80567
T2010	31.33333	14.16307	2.21	0.027	3.574223	59.09244
T2011	24	18.47901	1.30	0.194	-12.2182	60.2182
T2012	31	22.50156	1.38	0.168	-13.10224	75.10224
T2013	47.8	36.44708	1.31	0.190	-23.63496	119.235
T2014	61	43.85172	1.39	0.164	-24.94779	146.9478
T2015	71.4	49.38216	1.45	0.148	-25.38725	168.1872
T2016	90.8	50.31768	1.80	0.071	-7.820849	189.4208

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Pre_avg	.3	.4138461	0.72	0.469	-.5111235	1.111123
Post_avg	46.8141	11.36012	4.12	0.000	24.54868	69.07953
Tm11	-1	1.25e-16	-8.0e+15	0.000	-1	-1
Tm10	-2.25	2.394656	-0.94	0.347	-6.943439	2.443439
Tm9	3	1.369306	2.19	0.028	.3162088	5.683791
Tm8	2.5	1.274755	1.96	0.050	.0015263	4.998474
Tm7	-1	1.952562	-0.51	0.609	-4.826952	2.826952
Tm6	-2.75	2.294695	-1.20	0.231	-7.247519	1.747519
Tm5	8	3.181981	2.51	0.012	1.763433	14.23657
Tm4	-2.5	2.318405	-1.08	0.281	-7.04399	2.04399
Tm3	-2.9	2.818747	-1.03	0.304	-8.424642	2.624642
Tm2	1	2.45798	0.41	0.684	-3.817553	5.817553
Tm1	1.2	1.702743	0.70	0.481	-2.137315	4.537315
Tp0	1.4	3.34903	0.42	0.676	-5.163978	7.963978
Tp1	-1.2	2.079102	-0.58	0.564	-5.274966	2.874966
Tp2	3	3.437053	0.87	0.383	-3.7365	9.7365
Tp3	9	5.968808	1.51	0.132	-2.698648	20.69865
Tp4	15.8	6.950492	2.27	0.023	2.177287	29.42271
Tp5	15.25	9.311871	1.64	0.101	-3.000931	33.50093
Tp6	31.33333	14.16307	2.21	0.027	3.574223	59.09244
Tp7	33.66667	22.14075	1.52	0.128	-9.728413	77.06175
Tp8	53.33333	34.58859	1.54	0.123	-14.45905	121.1257
Tp9	85.66667	55.60642	1.54	0.123	-23.31992	194.6532
Tp10	103.6667	67.6319	1.53	0.125	-28.88942	236.2228
Tp11	115.6667	77.04304	1.50	0.133	-35.33491	266.6682
Tp12	142	76.81531	1.85	0.065	-8.555251	292.5553

Figure 13: Regression output - DealCount - cohort1 (g2004, g2011, g2012, g2017)

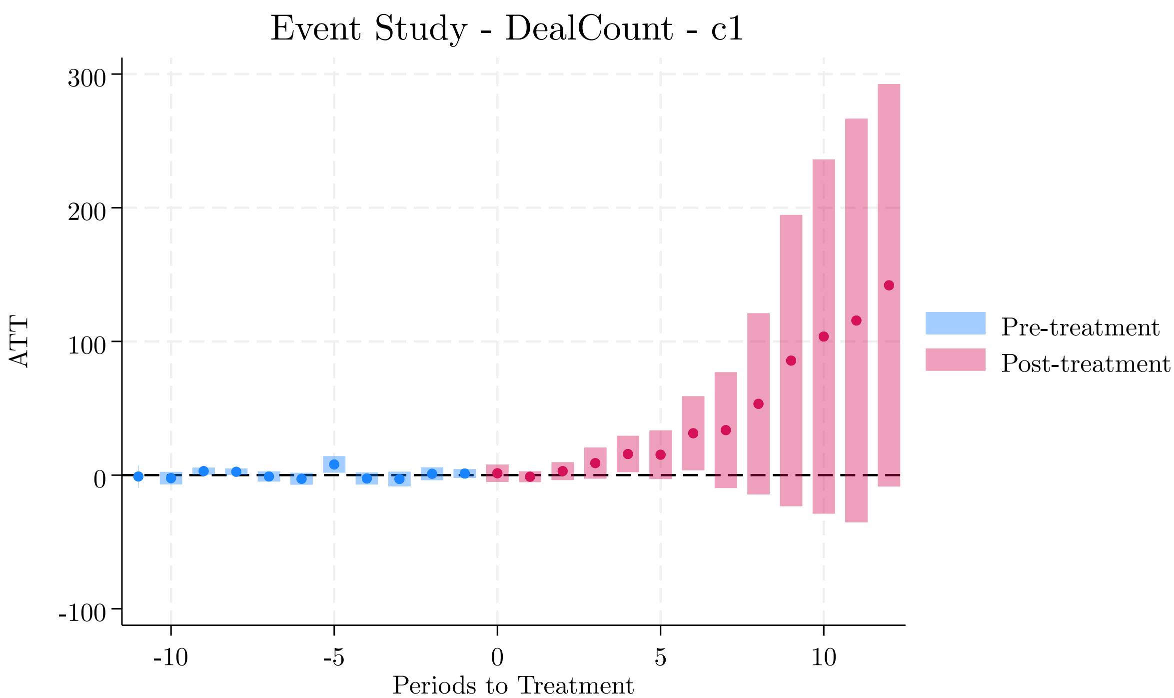

Figure 14: Regression output - DealCount - cohort1 (g2004, g2011, g2012, g2017) - Graph

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(12) = 12.4700
p-value = 0.4087
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
ATT	8.875	2.3961	3.70	0.000	4.17873	13.57127

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
GAverage	9.078788	1.944587	4.67	0.000	5.267468	12.89011
G2007	5.818182	2.850735	2.04	0.041	.2308437	11.40552
G2008	15.6	1.235314	12.63	0.000	13.17883	18.02117

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
CAverage	8.651515	2.184316	3.96	0.000	4.370335	12.9327
T2007	1.5	2.979094	0.50	0.615	-4.338917	7.338917
T2008	1.333333	1.677741	0.79	0.427	-1.954979	4.621645
T2009	3.333333	3.029179	1.10	0.271	-2.603749	9.270415
T2010	5.333333	2.275066	2.34	0.019	.8742856	9.792381
T2011	2.666667	2.175197	1.23	0.220	-1.596641	6.929974
T2012	5.333333	3.101672	1.72	0.086	-.7458324	11.4125
T2013	3.333333	4.379033	0.76	0.447	-5.249413	11.91608
T2014	10.66667	5.105371	2.09	0.037	.660323	20.67301
T2015	17	8.595865	1.98	0.048	.1524149	33.84759
T2016	18.66667	7.502469	2.49	0.013	3.962098	33.37124
T2017	26	12.99573	2.00	0.045	.5288455	51.47115

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Pre_avg	-.1904762	.446283	-0.43	0.670	-1.065175	.6842225
Post_avg	9.363636	2.706727	3.46	0.001	4.058549	14.66872
Tm7	-1	.	.	.	.	.
Tm6	2.666667	1.308802	2.04	0.042	.1014617	5.231872
Tm5	-.6666667	1.232282	-0.54	0.589	-3.081895	1.748561
Tm4	-3	.	.	.	.	.
Tm3	5	1.280191	3.91	0.000	2.490872	7.509128
Tm2	-4.333333	2.02987	-2.13	0.033	-8.311805	-.3548621
Tm1	0	3.46009	0.00	1.000	-6.781652	6.781652
Tp0	3	2.088327	1.44	0.151	-1.093046	7.093046
Tp1	3.666667	2.873893	1.28	0.202	-1.96606	9.299393
Tp2	2	2.339278	0.85	0.393	-2.584901	6.584901
Tp3	5.333333	2.275066	2.34	0.019	.8742856	9.792381
Tp4	2.666667	2.175197	1.23	0.220	-1.596641	6.929974
Tp5	6.666667	3.441307	1.94	0.053	-.0781707	13.4115
Tp6	4.666667	4.90559	0.95	0.341	-4.948113	14.28145
Tp7	13.33333	5.836507	2.28	0.022	1.89399	24.77268
Tp8	17.66667	8.70717	2.03	0.042	.6009265	34.73241
Tp9	19	7.566373	2.51	0.012	4.170181	33.82982
Tp10	25	19.47434	1.28	0.199	-13.16901	63.16901

Figure 15: Regression output - DealCount - cohort2 (g2007, g2008, g2018)

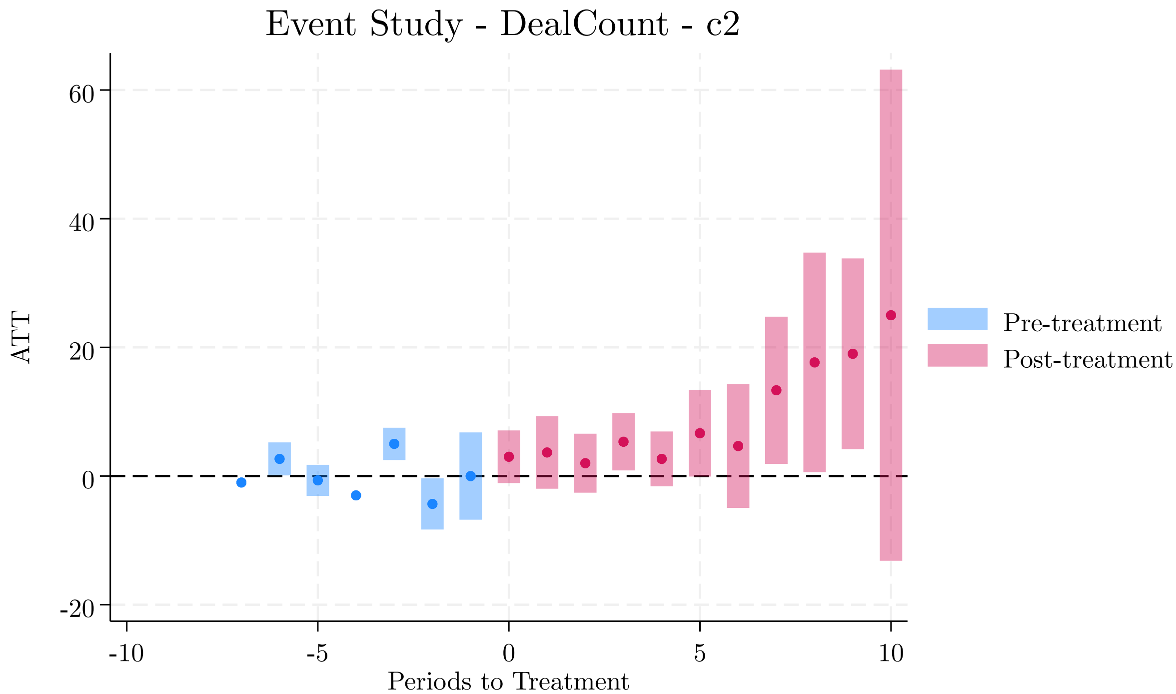

Figure 16: Regression output - DealCount - cohort2 (g2007, g2008, g2018) - Graph

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(18) = 10.8286
p-value = 0.9015
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ATT	3.484375	.8977013	3.88	0.000	1.724913	5.243837

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GAverage	3.253846	.7691157	4.23	0.000	1.746407	4.761285
G2004	4.641026	1.111335	4.18	0.000	2.462849	6.819203
G2007	1.4	1.461976	0.96	0.338	-1.465421	4.265421
G2012	2.8	.69857	4.01	0.000	1.430828	4.169172

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CAverage	3.041026	.8242165	3.69	0.000	1.425591	4.65646
T2004	.9166667	.8474499	1.08	0.279	-.7443046	2.577638
T2005	1.166667	1.826059	0.64	0.523	-2.412343	4.745676
T2006	-.4166667	1.178757	-0.35	0.724	-2.726988	1.893654
T2007	3.2	.9051703	3.54	0.000	1.425899	4.974101
T2008	1.6	1.037947	1.54	0.123	-.4343381	3.634338
T2009	1.3	1.05404	1.23	0.217	-.7658801	3.36588
T2010	2.9	2.142195	1.35	0.176	-1.298625	7.098625
T2011	.2	1.667133	0.12	0.905	-3.067521	3.467521
T2012	5	1.81238	2.76	0.006	1.4478	8.5522
T2013	5.333333	2.242271	2.38	0.017	.9385636	9.728103
T2014	9.333333	3.202646	2.91	0.004	3.056262	15.61041
T2015	8.166667	4.322636	1.89	0.059	-.3055449	16.63888
T2016	.8333333	2.778889	0.30	0.764	-4.613188	6.279855

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Pre_avg	-.015	.1021395	-0.15	0.883	-.2151897	.1851897
Post_avg	4.323077	1.026045	4.21	0.000	2.312066	6.334088
Tm10	-1	.	.	.	.	.
Tm9	1	.	.	.	.	.
Tm8	-2	.	.	.	.	.
Tm7	4	.	.	.	.	.
Tm6	-1.666667	.6938887	-2.40	0.016	-3.026663	-.3066699
Tm5	1	.3333333	3.00	0.003	.3466787	1.653321
Tm4	-1.333333	.3849002	-3.46	0.001	-2.087724	-.5789428
Tm3	1.083333	.7342088	1.48	0.140	-.3556894	2.522356
Tm2	-1.4	.8252777	-1.70	0.090	-3.017515	.2175146
Tm1	.1666667	.684019	0.24	0.807	-1.173986	1.507319
Tp0	1.625	.6932629	2.34	0.019	.2662297	2.98377
Tp1	1.916667	1.109069	1.73	0.084	-.2570692	4.090403
Tp2	1.625	1.246175	1.30	0.192	-.8174575	4.067458
Tp3	2.666667	.8079466	3.30	0.001	1.08312	4.250213
Tp4	.1666667	1.057381	0.16	0.875	-1.905763	2.239096
Tp5	1.5	.9192388	1.63	0.103	-.301675	3.301675
Tp6	3.5	2.203406	1.59	0.112	-.8185973	7.818597
Tp7	2	1.453731	1.38	0.169	-.8492601	4.84926
Tp8	5.4	2.18952	2.47	0.014	1.108619	9.691381
Tp9	2.8	2.966367	0.94	0.345	-3.013973	8.613973
Tp10	14	5.689496	2.46	0.014	2.848792	25.15121
Tp11	14.33333	7.784124	1.84	0.066	-.9232701	29.58994
Tp12	4.666667	4.996295	0.93	0.350	-5.125891	14.45922

Figure 17: Regression output - ExitCount - cohort1 (g2004, g2007, g2012, g2017)

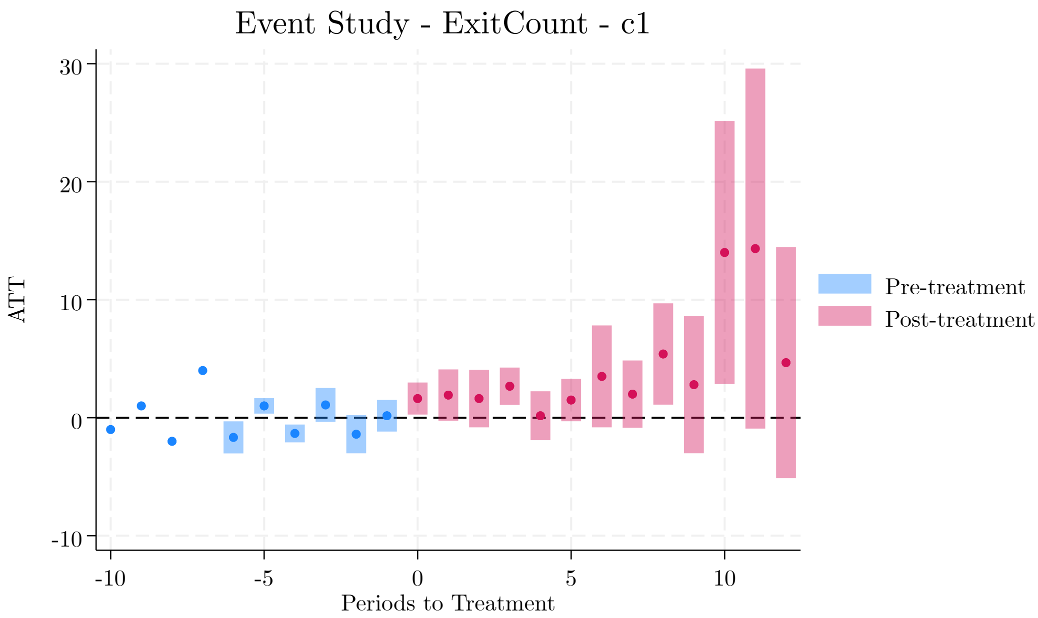

Figure 18: Regression output - ExitCount - cohort1 (g2004, g2007, g2012, g2017) - Graph

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(7) = 8.0000
p-value = 0.3326
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ATT	-.8387097	1.055855	-0.79	0.427	-2.908147	1.230727

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GAverage	-.7676768	.9788735	-0.78	0.433	-2.686234	1.15088
G2007	-1.318182	1.451928	-0.91	0.364	-4.163909	1.527545
G2008	.3333333	.4374449	0.76	0.446	-.5240429	1.19071

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CAverage	-.8787879	1.059957	-0.83	0.407	-2.956264	1.198689
T2007	-2.5	1.620185	-1.54	0.123	-5.675505	.6755046
T2008	-3.333333	1.01835	-3.27	0.001	-5.329263	-1.337404
T2009	-2	.942809	-2.12	0.034	-3.847872	-.1521282
T2010	-.5	1.457738	-0.34	0.732	-3.357114	2.357114
T2011	-1.666667	.9765775	-1.71	0.088	-3.580723	.2473902
T2012	-2.666667	1.084401	-2.46	0.014	-4.792054	-.5412794
T2013	2.333333	1.865873	1.25	0.211	-1.32371	5.990377
T2014	-1	1.013794	-0.99	0.324	-2.986999	.9869992
T2015	1	1.462494	0.68	0.494	-1.866436	3.866436
T2016	-1	1.301708	-0.77	0.442	-3.551301	1.551301
T2017	1.666667	1.347151	1.24	0.216	-.9737	4.307033

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Pre_avg	.3055556	.1753157	1.74	0.081	-.0380569	.649168
Post_avg	-.7878788	1.074797	-0.73	0.464	-2.894442	1.318684
Tm7	-2	.	.	.	.	.
Tm6	1	.	.	.	.	.
Tm4	.5	.3535534	1.41	0.157	-.1929519	1.192952
Tm3	1.5	1.06066	1.41	0.157	-.5788557	3.578856
Tm2	-.5	1.274755	-0.39	0.695	-2.998474	1.998474
Tm1	1.333333	1.071517	1.24	0.213	-.7668009	3.433468
Tp0	-2.333333	1.067187	-2.19	0.029	-4.424982	-.2416845
Tp1	-3.333333	1.01835	-3.27	0.001	-5.329263	-1.337404
Tp2	-2	1.414214	-1.41	0.157	-4.771808	.7718076
Tp3	-1	1.013794	-0.99	0.324	-2.986999	.9869992
Tp4	-1.333333	.9765775	-1.37	0.172	-3.24739	.5807235
Tp5	-.6666667	1.902727	-0.35	0.726	-4.395943	3.06261
Tp6	0	1.795055	0.00	1.000	-3.518243	3.518243
Tp7	1	1.301708	0.77	0.442	-1.551301	3.551301
Tp8	.3333333	1.272938	0.26	0.793	-2.161579	2.828245
Tp9	-1.333333	1.182433	-1.13	0.259	-3.65086	.984193
Tp10	2	2	1.00	0.317	-1.919928	5.919928

Figure 19: Regression output - ExitCount - cohort2 (g2007, g2008, g2018)

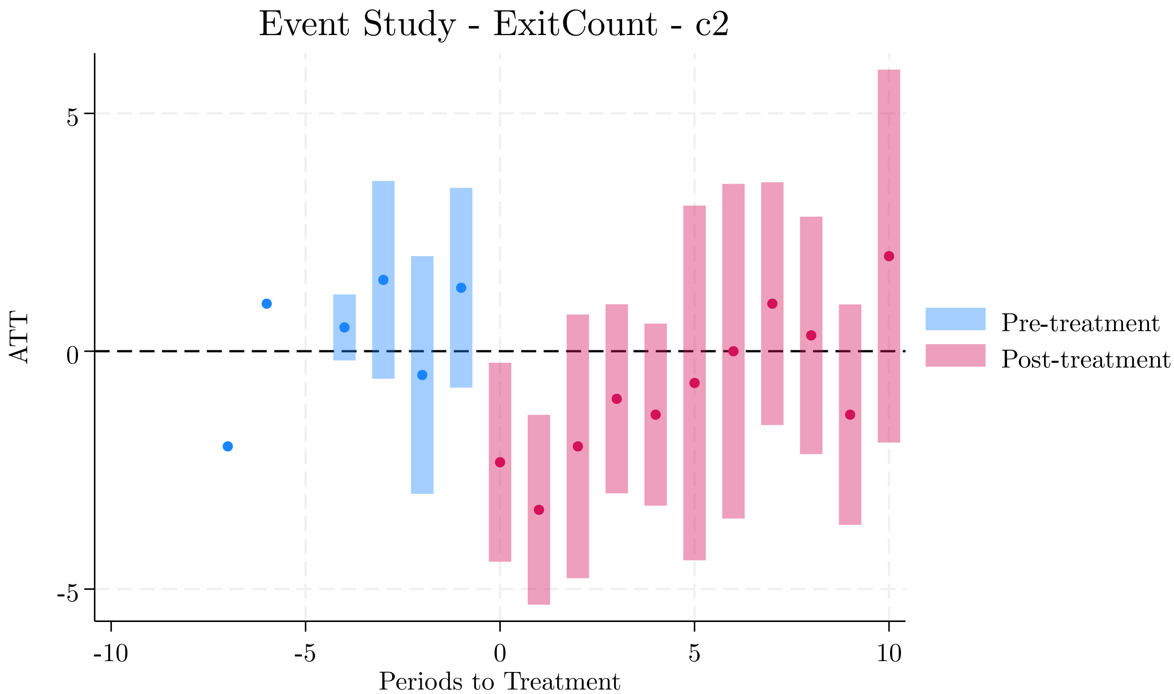

Figure 20: Regression output - ExitCount - cohort2 (g2007, g2008, g2018) - Graph

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(15) = 12.9838
p-value = 0.6036
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
ATT	.5969524	.1339561	4.46	0.000	.3344033	.8595014

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
GAverage	.6910204	.0976694	7.08	0.000	.4995919	.8824489
G2004	.5079365	.1441484	3.52	0.000	.2254108	.7904622
G2007	.6566667	.2860581	2.30	0.022	.0960032	1.21733
G2011	1	.	.	.	.	.
G2012	1	.	.	.	.	.

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
CAverage	.6022449	.1420671	4.24	0.000	.3237984	.8806914
T2004	.3333333	.2721655	1.22	0.221	-.2001013	.866768
T2005	.5238095	.5601687	0.94	0.350	-.574101	1.62172
T2006	1.380952	.7400493	1.87	0.062	-.0695177	2.831422
T2007	.36	.1856161	1.94	0.052	-.0038009	.7238009
T2008	.5	.25	2.00	0.046	.010009	.989991
T2009	.5	.25	2.00	0.046	.010009	.989991
T2010	.5	.25	2.00	0.046	.010009	.989991
T2011	.6666667	.2721655	2.45	0.014	.133232	1.200101
T2012	.6	.2780887	2.16	0.031	.0549561	1.145044
T2013	.6	.2780887	2.16	0.031	.0549561	1.145044
T2014	.8	.3864367	2.07	0.038	.042598	1.557402
T2015	.6666667	.2545875	2.62	0.009	.1676843	1.165649
T2016	.4	.2175623	1.84	0.066	-.0264142	.8264142
T2017	.6	.1932184	3.11	0.002	.221299	.978701

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Pre_avg	-.0107804	.0750525	-0.14	0.886	-.1578806	.1363197
Post_avg	.630989	.1449828	4.35	0.000	.346828	.9151501
Tm11	1	.	.	.	.	.
Tm10	-1	.	.	.	.	.
Tm7	1	.	.	.	.	.
Tm6	-.4583333	.2119478	-2.16	0.031	-.8737434	-.0429233
Tm5	-.4166667	.1751322	-2.38	0.017	-.7599195	-.0734138
Tm4	.6666667	.2721655	2.45	0.014	.133232	1.200101
Tm3	-.7053571	.6296101	-1.12	0.263	-1.93937	.5286561
Tm2	-.2166667	.0974917	-2.22	0.026	-.4077469	-.0255865
Tm1	.0333333	.2161532	0.15	0.877	-.3903192	.4569859
Tp0	.36	.1856161	1.94	0.052	-.0038009	.7238009
Tp1	.5142857	.3506817	1.47	0.143	-.1730378	1.201609
Tp2	1.028571	.4510737	2.28	0.023	.1444833	1.91266
Tp3	.5	.1734722	2.88	0.004	.1600008	.8399992
Tp4	.6666667	.2721655	2.45	0.014	.133232	1.200101
Tp5	1	.3333333	3.00	0.003	.3466787	1.653321
Tp6	1	.3333333	3.00	0.003	.3466787	1.653321
Tp7	1	.5	2.00	0.046	.020018	1.979982
Tp8	.4	.2175623	1.84	0.066	-.0264142	.8264142
Tp9	.4	.2175623	1.84	0.066	-.0264142	.8264142
Tp10	.6666667	.5443311	1.22	0.221	-.4002026	1.733536
Tp12	.3333333	.2721655	1.22	0.221	-.2001013	.866768
Tp13	.3333333	.2721655	1.22	0.221	-.2001013	.866768

Figure 21: Regression output - IPOCount (g2004, g2007, g2011, g2012, g2017, g2018)

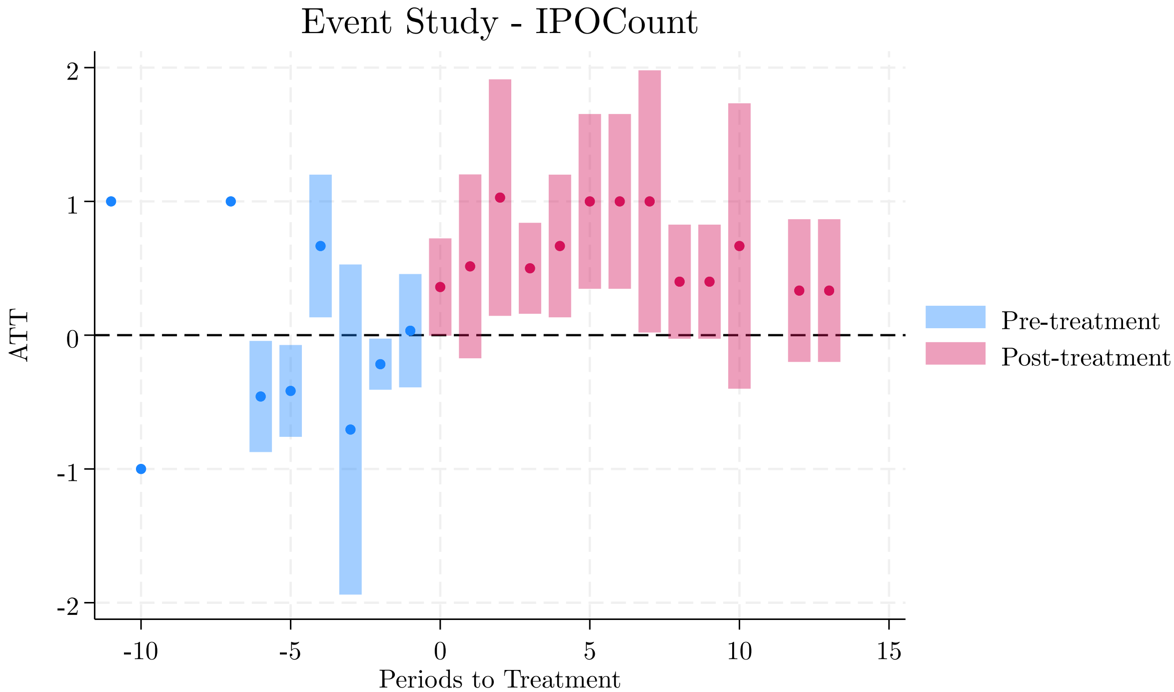

Figure 22: Regression output - IPOCount (g2004, g2007, g2011, g2012, g2017, g2018) - Graph

9.3 Regression output - excluding Berlin

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(22) = 19.5478
p-value = 0.6113
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
ATT	10.16216	3.538854	2.87	0.004	3.226135	17.09819

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
GAverage	7.762179	2.301875	3.37	0.001	3.250588	12.27377
G2004	14.30769	4.172743	3.43	0.001	6.129266	22.48612
G2011	-8.166667	1.711548	-4.77	0.000	-11.52124	-4.812093
G2012	10.6	3.12602	3.39	0.001	4.473114	16.72689

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
CAverage	9.326923	3.18716	2.93	0.003	3.080204	15.57364
T2004	-.8333333	3.693713	-0.23	0.822	-8.072879	6.406212
T2005	2	2.820231	0.71	0.478	-3.527551	7.527551
T2006	5.333333	6.329677	0.84	0.399	-7.072606	17.73927
T2007	5.666667	7.89456	0.72	0.473	-9.806386	21.13972
T2008	11.83333	10.58016	1.12	0.263	-8.903402	32.57007
T2009	9.833333	7.567902	1.30	0.194	-4.999483	24.66615
T2010	18.16667	13.40312	1.36	0.175	-8.102958	44.43629
T2011	5	11.52654	0.43	0.664	-17.5916	27.5916
T2012	4.5	5.412659	0.83	0.406	-6.108616	15.10862
T2013	4.75	8.932472	0.53	0.595	-12.75732	22.25732
T2014	9.5	10.32745	0.92	0.358	-10.74143	29.74143
T2015	13.25	6.785209	1.95	0.051	-.0487655	26.54877
T2016	32.25	15.9719	2.02	0.043	.9456529	63.55435

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
Pre_avg	.4608586	.4443501	1.04	0.300	-.4100515	1.331769
Post_avg	13.17735	3.730936	3.53	0.000	5.86485	20.48985
Tm11	-1	.	.	.	.	.
Tm10	-2.25	2.394656	-0.94	0.347	-6.943439	2.443439
Tm9	3	1.369306	2.19	0.028	.3162088	5.683791
Tm8	2.5	1.274755	1.96	0.050	.0015263	4.998474
Tm7	-1	1.952562	-0.51	0.609	-4.826952	2.826952
Tm6	-2.75	2.294695	-1.20	0.231	-7.247519	1.747519
Tm5	8	3.181981	2.51	0.012	1.763433	14.23657
Tm4	-2.5	2.318405	-1.08	0.281	-7.04399	2.04399
Tm3	-3.625	3.149556	-1.15	0.250	-9.798017	2.548017
Tm2	3.111111	2.385657	1.30	0.192	-1.56469	7.786912
Tm1	1.583333	2.045313	0.77	0.439	-2.425406	5.592073
Tp0	-1.166667	2.990485	-0.39	0.696	-7.027909	4.694575
Tp1	-2.5	2.125953	-1.18	0.240	-6.666791	1.666791
Tp2	1.416667	4.055781	0.35	0.727	-6.532519	9.365852
Tp3	4.583333	5.544668	0.83	0.408	-6.284017	15.45068
Tp4	11.91667	7.453075	1.60	0.110	-2.691091	26.52442
Tp5	4.888889	5.796888	0.84	0.399	-6.472803	16.25058
Tp6	18.16667	13.40312	1.36	0.175	-8.102958	44.43629
Tp7	10	13.80217	0.72	0.469	-17.05176	37.05176
Tp8	11.5	9.360823	1.23	0.219	-6.846875	29.84688
Tp9	18.5	14.9541	1.24	0.216	-10.80949	47.80949
Tp10	22	18.11767	1.21	0.225	-13.50998	57.50998
Tp11	21.5	10.05609	2.14	0.033	1.790421	41.20958
Tp12	50.5	27.63377	1.83	0.068	-3.661185	104.6612

Figure 23: Regression output - DealCount - cohort1 (g2004, g2011, g2012, g2017) – w/o Berlin

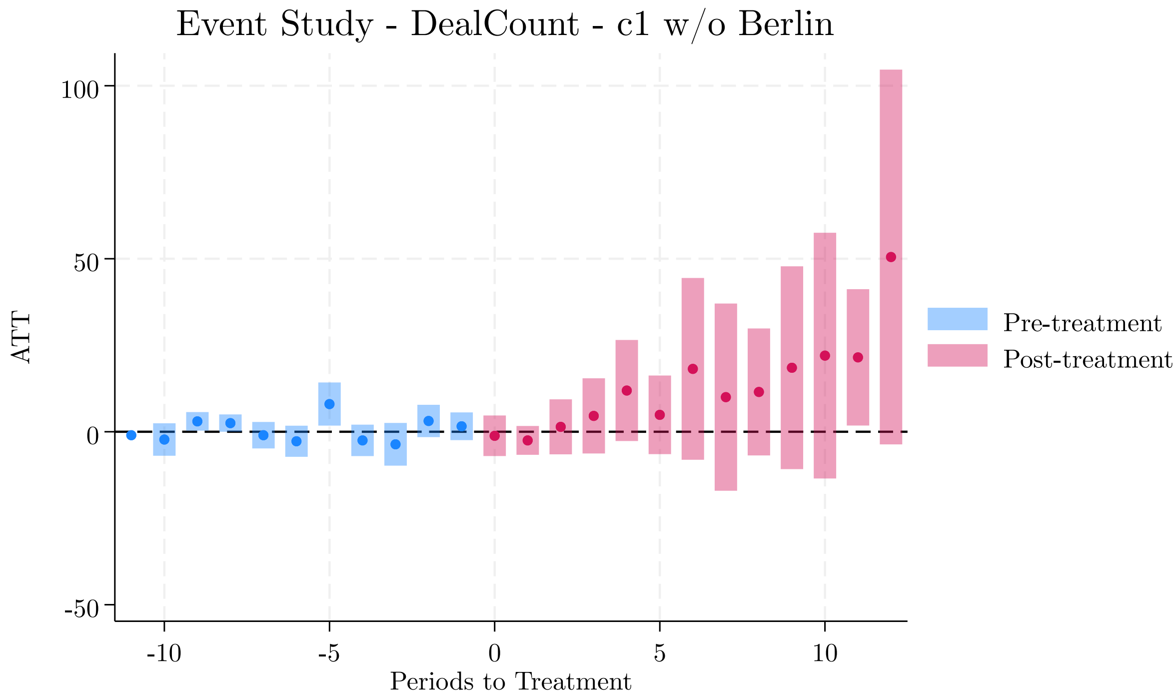

Figure 24: Regression output - DealCount - cohort1 (g2004, g2011, g2012, g2017) – w/o Berlin - Graph

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(17) = 11.5330
p-value = 0.8276
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ATT	1.836735	.7473541	2.46	0.014	.3719477	3.301522

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GAverage	1.92	.7058461	2.72	0.007	.536567	3.303433
G2004	2	.8102935	2.47	0.014	.411854	3.588146
G2007	1.4	1.461976	0.96	0.338	-1.465421	4.265421
G2012	2.8	.69857	4.01	0.000	1.430828	4.169172

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CAverage	1.611538	.7229122	2.23	0.026	.1946566	3.02842
T2004	1.25	.8196798	1.52	0.127	-.3565429	2.856543
T2005	2	2.284458	0.88	0.381	-2.477456	6.477456
T2006	-1.25	1.192424	-1.05	0.295	-3.587108	1.087108
T2007	2.5	.8838835	2.83	0.005	.7676202	4.23238
T2008	1.25	1.215139	1.03	0.304	-1.131628	3.631628
T2009	1.25	1.189144	1.05	0.293	-1.080679	3.580679
T2010	1.5	1.620185	0.93	0.355	-1.675505	4.675505
T2011	-.75	1.688657	-0.44	0.657	-4.059707	2.559707
T2012	3.4	1.56333	2.17	0.030	.3359299	6.46407
T2013	3.2	1.557562	2.05	0.040	.1472342	6.252766
T2014	5.8	1.648029	3.52	0.000	2.569922	9.030078
T2015	3.2	1.544668	2.07	0.038	.1725059	6.227494
T2016	-2.4	.8740709	-2.75	0.006	-4.113148	-.6868524

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Pre_avg	.045	.110306	0.41	0.683	-.1711957	.2611957
Post_avg	2.123077	.7743216	2.74	0.006	.6054344	3.640719
Tm10	-1	.	.	.	.	.
Tm9	1	.	.	.	.	.
Tm8	-2	.	.	.	.	.
Tm7	4	.	.	.	.	.
Tm6	-1.666667	.6938887	-2.40	0.016	-3.026663	-.3066699
Tm5	1	.3333333	3.00	0.003	.3466787	1.653321
Tm4	-1.333333	.3849002	-3.46	0.001	-2.087724	-.5789428
Tm3	2	.8333333	2.40	0.016	.3666967	3.633303
Tm2	-1.75	.9682458	-1.81	0.071	-3.647727	.147727
Tm1	.2	.8068457	0.25	0.804	-1.381389	1.781389
Tp0	1.9	.7134424	2.66	0.008	.5016787	3.298321
Tp1	2.4	1.161465	2.07	0.039	.1235712	4.676429
Tp2	1.7	1.368576	1.24	0.214	-.9823595	4.382359
Tp3	2	.7549834	2.65	0.008	.5202596	3.47974
Tp4	-.4	1.148913	-0.35	0.728	-2.651827	1.851827
Tp5	1.5	1.06066	1.41	0.157	-.5788557	3.578856
Tp6	3	2.54951	1.18	0.239	-1.996947	7.996947
Tp7	1.5	1.581139	0.95	0.343	-1.598975	4.598975
Tp8	3.5	2.015564	1.74	0.082	-.4504337	7.450434
Tp9	-.5	1.920286	-0.26	0.795	-4.263692	3.263692
Tp10	7.5	3.553168	2.11	0.035	.5359195	14.46408
Tp11	5	3.201562	1.56	0.118	-1.274946	11.27495
Tp12	-1.5	1.457738	-1.03	0.303	-4.357114	1.357114

Figure 25: Regression output - ExitCount - cohort1 (g2004, g2007, g2012, g2017) - w/o Berlin

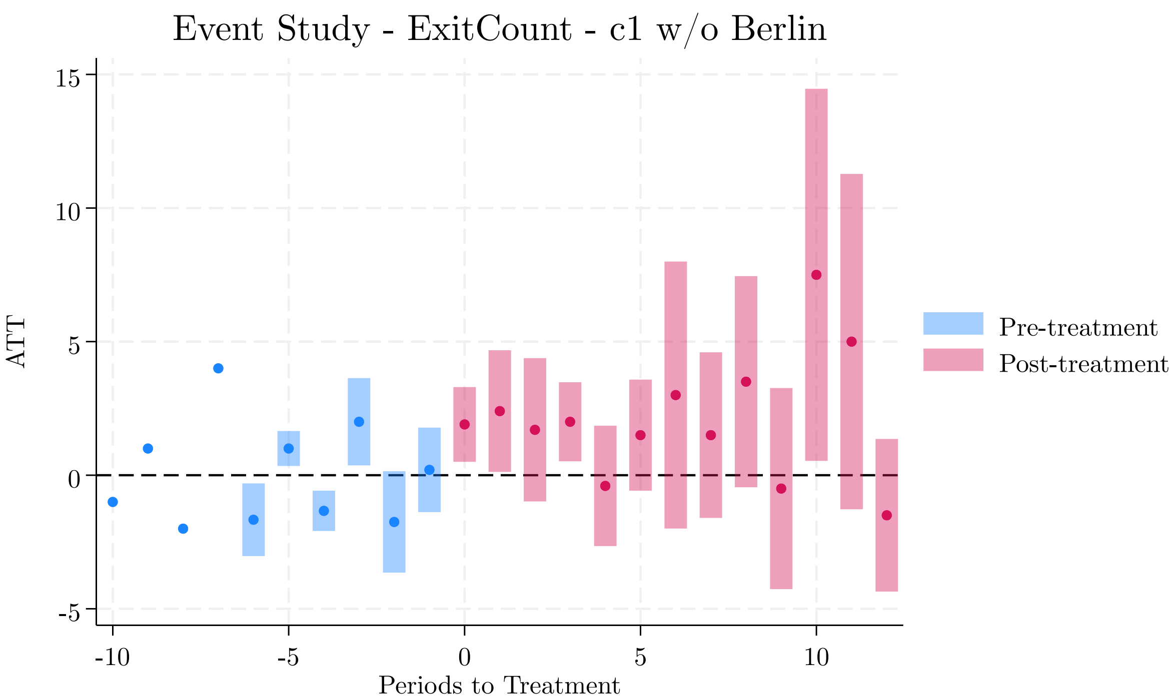

Figure 26: Regression output - ExitCount - cohort1 (g2004, g2007, g2012, g2017) - w/o Berlin - Graph

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(15) = 13.4871
p-value = 0.5647
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ATT	.7336617	.2116285	3.47	0.001	.3188774	1.148446

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GAverage	.8379365	.1704732	4.92	0.000	.5038152	1.172058
G2004	.8571429	.4507444	1.90	0.057	-.0263	1.740586
G2007	.6566667	.2860581	2.30	0.022	.0960032	1.21733
G2011	1	.	.	.	.	.
G2012	1	.	.	.	.	.

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CAverage	.7580586	.218885	3.46	0.001	.329052	1.187065
T2005	.8571429	.7193697	1.19	0.233	-.5527958	2.267081
T2006	1.214286	1.074316	1.13	0.258	-.8913346	3.319906
T2007	.45	.2087163	2.16	0.031	.0409235	.8590765
T2008	.5	.25	2.00	0.046	.010009	.989991
T2009	.5	.25	2.00	0.046	.010009	.989991
T2010	.5	.25	2.00	0.046	.010009	.989991
T2011	.6666667	.2721655	2.45	0.014	.133232	1.200101
T2012	1	.5	2.00	0.046	.020018	1.979982
T2013	1	.5	2.00	0.046	.020018	1.979982
T2014	1	.5	2.00	0.046	.020018	1.979982
T2015	.6666667	.2545875	2.62	0.009	.1676843	1.165649
T2016	.5	.3535534	1.41	0.157	-.1929519	1.192952
T2017	1	.	.	.	.	.

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Pre_avg	-.0421958	.0872197	-0.48	0.629	-.2131432	.1287517
Post_avg	.7202381	.2306291	3.12	0.002	.2682134	1.172263
Tm11	1	.	.	.	.	.
Tm10	-1	.	.	.	.	.
Tm7	1	.	.	.	.	.
Tm6	-.4583333	.2119478	-2.16	0.031	-.8737434	-.0429233
Tm5	-.4166667	.1751322	-2.38	0.017	-.7599195	-.0734138
Tm4	.6666667	.2721655	2.45	0.014	.133232	1.200101
Tm3	-.9880952	.7472493	-1.32	0.186	-2.452677	.4764866
Tm2	-.2166667	.0974917	-2.22	0.026	-.4077469	-.0255865
Tm1	.0333333	.2161532	0.15	0.877	-.3903192	.4569859
Tp0	.4	.219089	1.83	0.068	-.0294066	.8294066
Tp1	.6785714	.3859846	1.76	0.079	-.0779446	1.435087
Tp2	.8571429	.5464486	1.57	0.117	-.2138767	1.928162
Tp3	.6	.1843909	3.25	0.001	.2386005	.9613995
Tp4	.6666667	.2721655	2.45	0.014	.133232	1.200101
Tp5	1	.3333333	3.00	0.003	.3466787	1.653321
Tp6	1	.3333333	3.00	0.003	.3466787	1.653321
Tp7	1	.5	2.00	0.046	.020018	1.979982
Tp8	.5	.3535534	1.41	0.157	-.1929519	1.192952
Tp9	.5	.3535534	1.41	0.157	-.1929519	1.192952

Figure 27: Regression output - IPOCount (g2004, g2007, 2011, g2012, g2017, g2018) - w/o Berlin

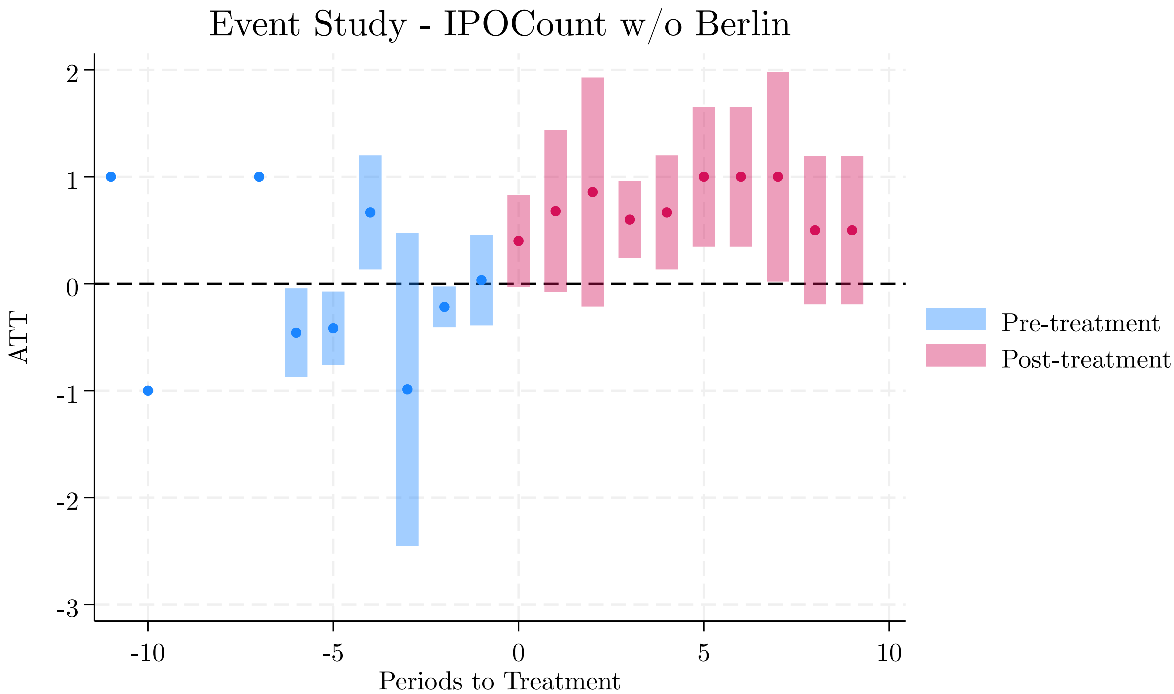

Figure 28: Regression output - IPOCount (g2004, g2007, 2011, g2012, g2017, g2018) - w/o Berlin – Graph

9.4 Further output

Pretrend Test. H0 All Pre-treatment are equal to 0
chi2(85) = 15677.1058
p-value = 0.0000
Average Treatment Effect on Treated

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ATT	56.7367	11.40611	4.97	0.000	34.38113	79.09227

ATT by group

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
GAverage	44.12964	5.407006	8.16	0.000	33.5321	54.72717
G2004	114.6437	19.45932	5.89	0.000	76.50413	152.7832
G2007	13.80952	4.192621	3.29	0.001	5.592138	22.02691
G2008	25.93542	2.143721	12.10	0.000	21.7338	30.13703
G2011	-4.8375	.8869443	-5.45	0.000	-6.575879	-3.099121
G2012	58.35417	6.628802	8.80	0.000	45.36195	71.34638
G2017	17.52381	1.549153	11.31	0.000	14.48752	20.56009
G2018	11.5	1.405594	8.18	0.000	8.745086	14.25491
G2019	5.4	1.23774	4.36	0.000	2.974074	7.825926

ATT by Calendar Period

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
CAverage	45.68163	9.599494	4.76	0.000	26.86697	64.49629
T2004	4.222222	4.038566	1.05	0.296	-3.693221	12.13767
T2005	2.444444	1.826493	1.34	0.181	-1.135416	6.024305
T2006	7.666667	4.387287	1.75	0.081	-.9322574	16.26559
T2007	8.885714	5.540133	1.60	0.109	-1.972747	19.74418
T2008	10.75	5.738241	1.87	0.061	-.4967449	21.99674
T2009	13.75	6.440188	2.14	0.033	1.127464	26.37254
T2010	18.91667	8.565602	2.21	0.027	2.128396	35.70494
T2011	18.11429	10.96258	1.65	0.098	-3.371976	39.60055
T2012	24.09375	14.61866	1.65	0.099	-4.5583	52.7458
T2013	35.46875	23.65501	1.50	0.134	-10.89422	81.83172
T2014	46.21875	28.41687	1.63	0.104	-9.477294	101.9148
T2015	52.46875	31.9148	1.64	0.100	-10.08312	115.0206
T2016	66.09375	32.88223	2.01	0.044	1.645773	130.5417
T2017	69.88889	32.95089	2.12	0.034	5.306326	134.4715
T2018	69.75	34.0007	2.05	0.040	3.109849	136.3902
T2019	69.36364	34.73761	2.00	0.046	1.279179	137.4481
T2020	85.9	38.1404	2.25	0.024	11.14618	160.6538
T2021	111.9091	52.18277	2.14	0.032	9.632738	214.1854
T2022	107	54.33137	1.97	0.049	.5124785	213.4875
T2023	90.72727	40.97745	2.21	0.027	10.41294	171.0416

ATT by Periods Before and After treatment
Event Study:Dynamic effects

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Pre_avg	-.0437988	.1594578	-0.27	0.784	-.3563304	.2687328
Post_avg	87.38674	15.89596	5.50	0.000	56.23123	118.5422
Tm18	-1	.	.	.	.	.
Tm17	-1.25	1.198958	-1.04	0.297	-3.599914	1.099914
Tm16	-.6111111	.3040084	-2.01	0.044	-1.206957	-.0152655
Tm15	.7222222	.1994505	3.62	0.000	.3313063	1.113138
Tm14	.6111111	.7851284	0.78	0.436	-.9277123	2.149935
Tm13	.9166667	1.326589	0.69	0.490	-1.6834	3.516733
Tm12	-1	.8221471	-1.22	0.224	-2.611379	.6113788
Tm11	.9791667	.8659314	1.13	0.258	-.7180277	2.676361
Tm10	-2.466667	1.043348	-2.36	0.018	-4.51159	-.4217431
Tm9	1.836667	.7696601	2.39	0.017	.3281606	3.345173
Tm8	.2666667	.7480268	0.36	0.721	-1.199439	1.732772
Tm7	.1458333	1.405785	0.10	0.917	-2.609454	2.90112
Tm6	.1672619	.9646596	0.17	0.862	-1.723436	2.05796
Tm5	2.64881	1.267908	2.09	0.037	.1637555	5.133864
Tm4	-1.538988	.7901747	-1.95	0.051	-3.087702	.0097258
Tm3	-.3878788	1.349339	-0.29	0.774	-3.032534	2.256776
Tm2	-.5051948	1.086284	-0.47	0.642	-2.634273	1.623883
Tm1	-.3229437	1.017191	-0.32	0.751	-2.316601	1.670714
Tp0	3.740043	1.519427	2.46	0.014	.7620217	6.718065
Tp1	3.340909	1.471414	2.27	0.023	.4569908	6.224827
Tp2	6.037879	1.829788	3.30	0.001	2.451561	9.624197
Tp3	10.00346	2.919575	3.43	0.001	4.281201	15.72573
Tp4	14.65909	3.600723	4.07	0.000	7.601803	21.71638
Tp5	16.875	4.806332	3.51	0.000	7.454763	26.29524
Tp6	21.94444	6.565167	3.34	0.001	9.076953	34.81194
Tp7	27.0375	9.213816	2.93	0.003	8.978753	45.09625
Tp8	35.375	14.97956	2.36	0.018	6.015603	64.7344
Tp9	63.52381	26.21722	2.42	0.015	12.139	114.9086
Tp10	72.55208	28.76558	2.52	0.012	16.17258	128.9316
Tp11	69.53125	31.96734	2.18	0.030	6.87642	132.1861
Tp12	76.21429	37.67314	2.02	0.043	2.376284	150.0523
Tp13	103.3333	46.74109	2.21	0.027	11.72249	194.9442
Tp14	105.8333	54.33851	1.95	0.051	-.6681882	212.3349
Tp15	113.6667	60.23132	1.89	0.059	-4.384561	231.7179
Tp16	139.4	72.10137	1.93	0.053	-1.916085	280.7161
Tp17	301.6667	165.9942	1.82	0.069	-23.67598	627.0093
Tp18	309.6667	170.5347	1.82	0.069	-24.57515	643.9085
Tp19	253.3333	125.2381	2.02	0.043	7.871083	498.7956

Figure 29: Regression output - DealCount (g2004, g2007, g2008, g2011, g2012, g2017, g2018, g2019, g2024)

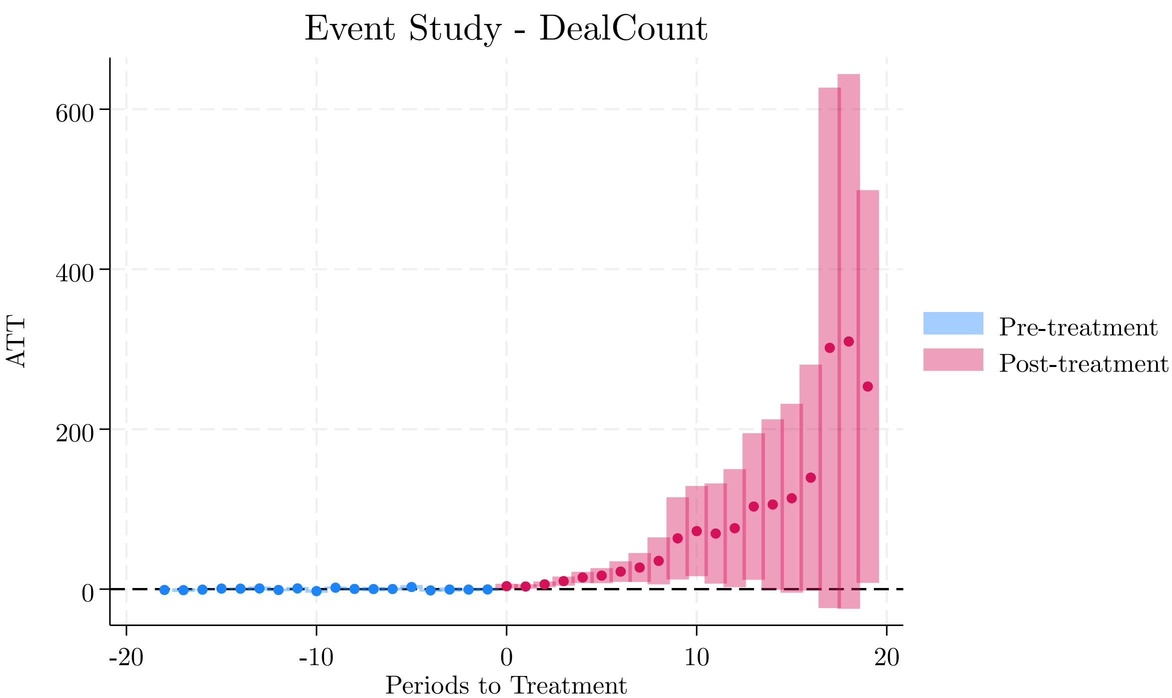

Figure 30: Regression output - DealCount (g2004, g2007, g2008, g2011, g2012, g2017, g2018, g2019, g2024) – Graph

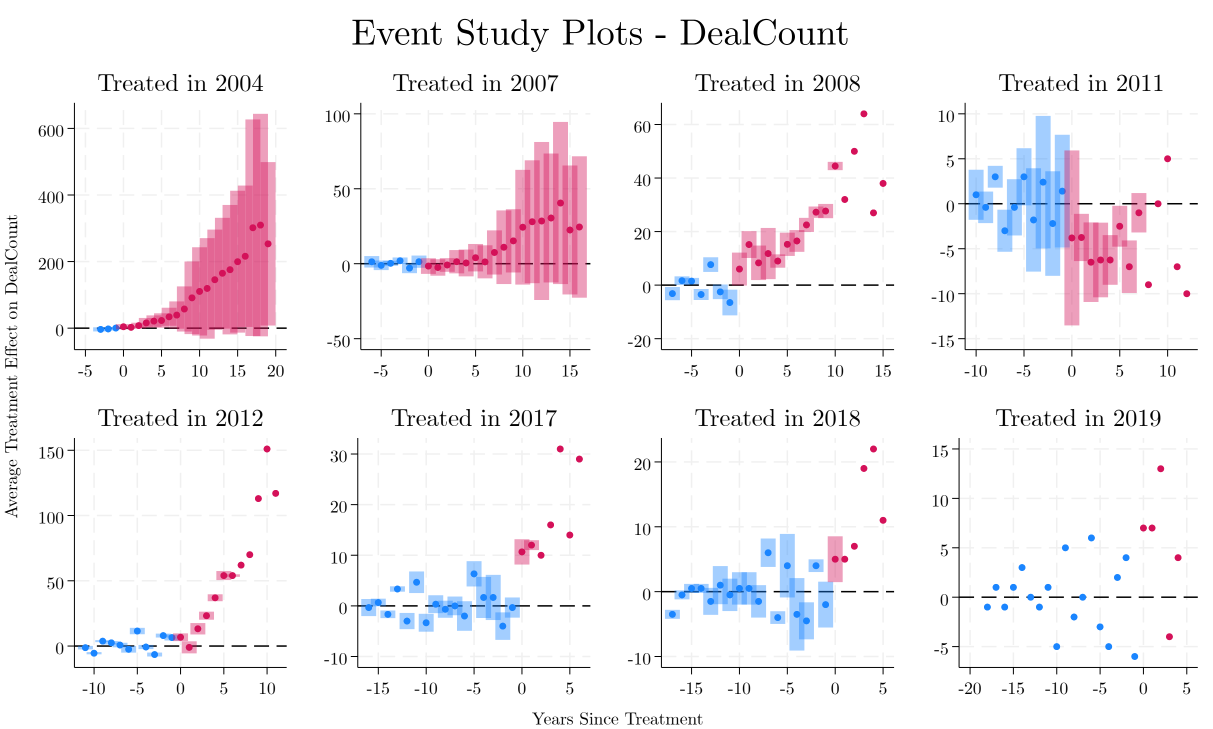

Figure 31: Regression output - DealCount (g2004, g2007, g2008, g2011, g2012, g2017, g2018, g2019, g2024) – Graph by group