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How do political connections of firms matter during an economic crisis?☆

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ABSTRACT

We use a new machine learning-enabled, *social network based* measurement technique to assemble a novel dataset of firms' political connections in India. Combining it with a long panel of detailed financial transactions of firms, we study *how* firms leverage these connections during an economic downturn. Using a synthetic difference-in-differences framework, we find that connected firms had 8%–10% higher income, sales, and TFPR gains that were persistent for over a three-year period following the crisis. We unpack various novel mechanisms and show that connected firms were able to decrease expensive long-term borrowings from banks in favor of short-term non-collateral ones, increase borrowing from the government, delay their short-term payments to suppliers and creditors, delay debt and interest payments, and increase investments in productive assets such as computers and software. Our method to determine political connections is portable to other applications and contexts.

1. Introduction

The role of political connections in running businesses has been widely acknowledged and politically connected firms operate in all countries across the world, including those with strong institutions and low levels of corruption.[1] This nexus between business and government however has always been an area of active policy interest and debate. The economic literature has documented the benefits of having a political connection, either through access to better finance, taxation benefits, public contracts, lower regulatory oversight, etc., and its resulting impact on firm survival, valuation, profits, and growth.[2]

There is little empirical evidence, however, on how these political connections matter during economic downturns when resources available in the economy are scarce. Understanding the role of political connections during a crisis has become especially relevant, given that the world has experienced two of the worst economic downturns since the Great Depression in a span of a decade—the Global Financial Crisis and more recently, the Covid-19 pandemic. In theory, political connections could help firms exert their influence over the bureaucratic machinery during a crisis and divert scarce resources towards them. Alternately, the political system could leverage these connections to drain resources from firms instead, as rent-seeking incentives become more acute during an economic downturn (Shleifer and Vishny, 1994). In addition to this, a second question that has received even lesser attention – primarily due to data constraints – is the mechanisms through which political connections impact firm performance. For example, do connected firms systematically alter their borrowings and liabilities portfolio during a crisis, and use it to invest in assets? Does it lead to differential changes in firm performance and growth after the crisis? Using a long panel of firms, with detailed data on their sales, income, and expenses, as well as their portfolio of assets, liabilities, and borrowings, this paper provides answers to both of these questions in the context of an unexpected macroeconomic shock in India in 2016.

A central novel contribution of this study is the construction of a new *social network based* measure of firms' political connections, using a new dataset that we assemble. This measurement relies on

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[1] Faccio et al. (2006), Tihanyi et al. (2019), Amore and Bennedsen (2013), Acemoglu et al. (2016).

[2] De Soto (1989), Stiglitz and Dasgupta (1971), Fisman (2001), Sapienza (2004), Khwaja and Mian (2005), Dinç (2005), Faccio, Masulis, and McConnell (2006), Goldman, Rocholl, and So (2008), Akcigit, Baslandze, and Lotti (2023), Choi, Penciakova, and Saffie (2021), Heitz, Wang, and Wang (2021).

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0304-3878/

machine learning algorithms and can be adapted to other settings. In our context, the creation of the data is based on the following steps: first, we collect comprehensive information on not only politicians who have ever contested elections but also the universe of active and retired bureaucrats in the Indian Administrative Services (IAS). Second, we obtain data on the universe of registered firms (and their Boards of Directors) from the Ministry of Corporate Affairs. Third, we use over 5 million news articles from seven leading media outlets and Wikipedia pages for these individuals. We then implement sophisticated machine learning algorithms and entity resolution mechanisms to search and curate their interviews, announcements, and appearances at personal and professional events. This allows us to ascertain if politicians and bureaucrats themselves, or their kin, friends, or social contacts have ever served as Directors in any of these firms.

Our measurement of political connections therefore, improves on some of the most common ones in the literature in three significant ways: first, as opposed to coarse measures (like co-ethnic or regional associations, social or gender identities, etc.), we observe a more direct connection to the government | politicians and bureaucrats who are directors in firms. Second, our machine learning algorithm relies on "context-based" matching in addition to "string-based" matching alone. This enables us to significantly reduce both Type-I (false positives) and Type-II (false negatives) errors from a name-matching exercise alone that is commonly used in the literature (see Section 3.3 for details). Third, our algorithm is able to capture *indirect* connections between politicians/bureaucrats and Directors through their personal, professional, and social networks such as friendships, meetings, and social appearances as reported in the media. These connections account for around 13% of the political connections in our sample and would be completely missed in a standard method that identifies connections coarsely or through name-matching algorithms.

A firm is therefore politically connected if one or more of its Directors: (i) is or ever was a politician/bureaucrat; (ii) is a kin or relative of a politician/bureaucrat; (iii) connected through friendships as well as professional and social interactions reported in the media (Section 3 provides a more detailed discussion). For our empirical analysis, we define a time-invariant binary variable that takes the value 1 if a firm in the pre-crisis period (discussed below) is politically connected and 0 otherwise.[3] By this definition, 2.75% of firms in our sample are politically connected.[4]

The empirical context is India's Demonetization episode of 2016. In a completely surprising announcement, India's Prime Minister demonetized 86% of India's currency overnight in November 2016. This led to massive cash and credit shortages across the country, as the banking system grappled with replenishing the economy with the new currency bills gradually over time (Chodorow-Reich et al., 2020). The resulting disruptions and delays severely impacted both households and firms, and economic recovery was slow even a couple of years after this episode (Lahiri, 2020; Karmakar and Narayanan, 2020). It is in this context that our study examines how politically connected firms, as compared to their non-connected counterparts, systematically differed in their response to the crisis and the potential role of these connections in altering the portfolio of assets, liabilities, and operational decisions of a firm.

We use rich data on a panel of over 30,000 formal sector firms across all major Indian states between 2012–2019. These data are obtained from the Prowess Data of the Center for Monitoring the Indian Economy (CMIE). Even though the data covers large firms in the formal sector, a unique feature is that it harmonizes detailed information on firm operations by using their Annual Reports, Quarterly Financial Statements, and other publicly available sources. We can therefore observe the composition of asset, liability, and borrowing portfolios of a firm, along with the more aggregate categories like income, sales, and expenses. We use this information to examine various channels through which firms leverage their political connections in response to the crisis.

It is important to note that politically connected firms in our sample are older and larger in size as compared to their non-connected counterparts (see Table 1). Consequently, they have higher income, sales, expenses (wage and capital bills) as well as assets and liabilities even before the crisis. While this pattern is consistent for India as well as across countries (Faccio, 2010; Bhalla et al., 2022), it raises the concern on whether firms' response to the crisis can be explained by the *selection* of firms who acquire political connections (such as those with higher entrepreneurial ability, better resilience to shocks, etc.), or political connections themselves. In order to address this, our identification strategy implements a Synthetic Difference-in-Differences (SDID) methodology. Recently developed by Arkhangelsky et al. (2021), SDID combines insights from Difference-in-Differences (DID) and Synthetic Control (SC) methods (Abadie et al., 2010) by: (i) re-weighting and matching pre-exposure *trends* between the treated and control units on the outcome variables (similar to SC); and (ii) allowing for the additive unit- and time-specific *selection* into the treatment (similar to DID). These fixed effects, therefore, control for all observable and unobservable time-invariant differences in *levels* across connected (treated) and non-connected (control) firms (such as the entrepreneurial ability for example). Moreover, by construction, we generate a "synthetic control" group of firms that have similar *trends* to the treated (connected) firms in the years prior to the crisis (pre-period).[5] In a nutshell, therefore, firm fixed effects absorb all time in-variant differences that influence firms' *selection* into acquiring political connections, while creating synthetic control units alleviates concerns about time-varying unobservables that could bias our results. In addition to this, a long panel of firms allows us to also control for district×year and industry×year fixed effects in our analysis. These control for all observable and unobservable time-varying changes across districts and industries that could impact firm outcomes, or be correlated with the demonetization shock (such as district- or industry-specific changes in prices and wages, supply and credit disruptions, etc.). In what follows, we first discuss the results, followed by mechanisms, and finally, multiple additional robustness tests that rule out alternate explanations and reaffirm the role of firms' political connections in driving the results.

We begin by documenting that politically connected firms (as compared to their non-connected counterparts) reported 8%–11% higher income, sales, and expenses after the macroeconomic crisis. Moreover, these effects persisted over three years following demonetization. It is unclear just from these estimates whether connected firms were more *robust* to the crisis i.e., firm outcomes (sales, for example) were impacted less due to the crisis; or were more *resilient* as well i.e., were impacted less, but also recovered faster (Khanna et al., 2022). We find evidence in favor of the latter | connected firms (relative to non-connected ones) had a lower decline in sales, followed by faster growth in them after the crisis (Figure D1). Politically connected firms also exhibited around a 5% higher TFPR as compared to non-connected ones.[6] A large literature discusses the source of these productivity gains (TFPR), predominantly along three dimensions: (i) gains in the

[3] While it rule it out by definition for the main analysis, we examine how firms who acquire connections after the crisis impact our analysis in Section 8.5.

[4] While we study a different sample, our estimate is in line with Faccio (2006), who examines firms' political connections using a similar methodology across 47 countries, including India.

[5] Using event studies, we show that there are no pre-trends in income, sales, and expenses in for the treated and the synthetic control units.

[6] A long panel of firms allows us to construct measures of TFP using standard methods from the literature. In particular, we first calculate Revenue Total Factor Productivity (TFPR) measures using the method proposed by Levinsohn and Petrin (2003).

Table 1
Summary Statistics (2012~2015).

	(1) Unconnected		(2) Connected		t-test Difference
	N/Firms	Mean/SD	N/Firms	Mean/SD	(1)-(2)/SE
Total Income (USD Million)	81,655	31.348	2,886	119.050	−87.702***
	(28,171)	(85.840)	(834)	(196.981)	(1.740)
Sales (USD Million)	81,655	28.717	2,886	102.308	−73.591***
	(28,171)	(80.310)	(834)	(179.630)	(1.622)
Total Expenses (USD Million)	81,655	31.120	2,886	113.570	−82.450***
	(28,171)	(84.134)	(834)	(183.911)	(1.693)
Ln(TFPR1)	69,399	0.775	2,012	0.877	−0.111***
	(25,602)	(1.020)	(630)	(1.122)	(0.023)
Ln(TFPR2)	69,399	0.630	2,012	0.835	−0.205***
	(25,602)	(1.359)	(630)	(1.450)	(0.031)
Firm's age	81,655	21.516	2,886	26.820	−5.304***
	(28,171)	(16.668)	(834)	(18.679)	(0.317)
Listed on BSE/NSE	81,655	0.157	2,886	0.278	−0.122***
	(28,171)	(0.364)	(834)	(0.448)	(0.007)
Annual avg. value of total transactions in BSE (USD Million)	81,655	20.122	2,886	158.498	−138.376***
	(28,171)	(411.331)	(834)	(1173.293)	(8.688)
Annual avg. value of total transactions in NSE (USD Million)	81,655	55.935	2,886	487.435	−431.499***
	(28,171)	(1090.454)	(834)	(3257.380)	(23.279)
Value added tax (USD Million)	81,655	0.013	2,886	0.024	−0.011*
	(28,171)	(0.316)	(834)	(0.282)	(0.006)
rK (USD Million)	81,410	30.264	2,869	230.804	−200.540***
	(28,111)	(197.412)	(830)	(613.204)	(4.266)
wL (USD Million)	81,166	2.557	2,878	11.746	−9.188***
	(28,075)	(11.711)	(833)	(24.798)	(0.235)
Financial Statistics					
Total assets (USD Million)	81,638	57.595	2,886	375.139	−317.544***
	(28,167)	(294.025)	(834)	(911.199)	(6.334)
Total Liabilities (USD Million)	81,655	56.955	2,886	370.355	−313.400***
	(28,171)	(285.147)	(834)	(884.745)	(6.145)
Total Borrowings (USD Million)	79,583	22.231	2,880	154.145	−131.913***
	(27,749)	(157.630)	(834)	(455.980)	(3.352)

Notes: wL = Compensations to employees. TFPR = Total factor revenue productivity. rK = Non-current assets. CL = Current liabilities. See Section A in the Appendix for detailed definitions of variables. India introduced the Goods and Services Tax in 2017, so it is not included in the summary statistics table above. In the last column, we test the differences between politically non-connected and connected firms using a t-test with equal variance. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

quantity efficiency as measured by TFPQ (De Loecker, 2011); (ii) price markups; (iii) change in firm capability as measured by product quality and scope (Atkin et al., 2019). With some caveats discussed in Section 6.2, we find no TFPQ differences between politically connected and non-connected firms after demonetization. Instead, connected firms reported a larger product scope.

A key question that naturally arises from the above analysis is: what did connected firms do differently to be able to realize these gains? We leverage our rich data to unpack several mechanisms.[7] First, we examine changes in credit and borrowings, the most common channel documented in the literature.[8] We find that politically connected firms reported lower borrowings as compared to their non-connected counterparts after the crisis (by 5%). However, we find a shift in the composition of their debt across loan duration (short vs. long), borrowing type (secured vs. unsecured), and borrowing source (banks vs. government). Given the rise in interest rates following the demonetization shock (see Appendix Section F for details), connected firms were able to reduce their now-costlier long-term borrowings, particularly from banks, by substituting them with long-term loans from government sources instead. Second, connected firms more generally skewed their borrowings portfolio towards more short-term loans, particularly from state and central governments directly. Lastly, connected firms were more likely to secure uncollateralized loans as well, potentially by leveraging their political connections.

We further harness our data to uncover other novel channels that have not been documented in the literature. In particular, we find that politically connected firms (compared to their non-connected counterparts) increased their liabilities (by 5.5%) after demonetization, and in particular, increased short-term liabilities (expected to be repaid within a year) as opposed to longer-term ones. This increase in short-term liabilities was driven by delaying payments to suppliers and vendors, as well as interest and debt payments to creditors due within the next year.

How did these differential changes in borrowings and liabilities impact the portfolio of assets? We find that as compared to their non-connected counterparts, connected firms were able to expand both the size and composition of their asset portfolio after demonetization. In particular, connected firms (relative to non-connected ones) reported a 4.1% increase in total assets, with a comparable increase in both their short-term and long-term assets.[9] Despite the large macroeconomic shock, these connected firms were able to increase both their short and long-term investments as well as incur higher expenditure on intangible commodities (such as computer software, patents, marketing rights, etc.), which is consistent with the productivity gains we document earlier. Connected firms were also more likely to acquire other firms, especially in the year following the crisis. On the other hand, we find no relative difference in changes to short-term inventories, bank balance, expenditure on fixed assets, or on plant, property, and machinery

[7] We provide detailed definitions of all variables used in our analysis in Appendix Section A.

[8] See Khwaja and Mian (2005), Charumilind et al. (2006), Claessens et al. (2008), Faccio et al. (2006).

[9] Short-term or current assets are those assets that can be easily converted to cash within 12 months, while long-term or non-current assets cannot be converted to cash within 12 months. They include capital work, fixed assets, etc. Please see Appendix Section A for detailed definitions of all variables.

between connected and non-connected firms. Put together, our results suggest that firms used political connections to get access to scarce (potentially uncollateralized) credit, delay their short-term payments to creditors and suppliers, accumulate productive assets, and acquire other firms, leading to better resilience after the crisis.

We undertake multiple additional analyses to rule out alternate explanations and increase our confidence in the causal interpretation of our results. First, we find no evidence that connected firms had prior knowledge about the government's plan to demonetize. Differences between these firms only appear (and are persistent) after demonetization. Second, we create alternate, broader measures of a firm's connections through its Board of Directors: for each firm, we calculate the average number of other firms their Directors are on the Board of, as well as other Directors that they would know through them. We find that while being "connected" more generally matters for firms' resilience to the crisis, the impact of having a *political* connection is very robust and an order of magnitude more important (see Section 8.2 for details).[10] Third, firms with indirect political connections, through directors serving on boards of politically connected firms, performed no better than non-connected firms after the crisis, again pointing to the importance of direct political connections. Fourth, following the literature (Faccio et al., 2006; Deng et al., 2020), we show that recent, newer connections matter more than older ones. Fifth, we find no evidence that our effect is driven by larger firms, who would also be more likely to acquire political connections. In other words, if firm, entrepreneur, or director characteristics were driving our results (as opposed to the political connections themselves), the above channels should have played a role in explaining firm resilience to the crisis, but we do not find evidence of any. Lastly, we check whether politically connected firms were located in areas with less severe shocks, operating in industries that were more downstream (and hence more impacted by the shock), or acquired connections after the crisis, which could rationalize the results, but find no evidence in support of this either.

Our paper complements and extends rich literature that studies the impact of political connections on firm performance. While some studies (Faccio et al., 2006; Faccio, 2010; Niessen and Ruenzi, 2010; Bertrand et al., 2018) show that politically connected firms underperform compared to non-connected firms and political connections are costly, others (Acemoglu et al., 2016; Goldman et al., 2009; Boubakri et al., 2012; Amore and Bennedsen, 2013; Houston et al., 2014; Brown and Huang, 2020) argue that firms benefit from political connections. Most of the literature has focused on channels through which firms might benefit from acquiring political connections, such as a higher likelihood of receiving credit loans (Khwaja and Mian, 2005; Charumilind et al., 2006; Claessens et al., 2008; Li et al., 2008), getting corporate bailouts (Faccio et al., 2006), winning public contracts (Goldman et al., 2008), and facing lower regulatory enforcement (Houston et al., 2014).

We extend this literature in a number of ways. First, our study complements prior work by Acemoglu et al. (2016) and Carney et al. (2020), who examine the role of political connections during crises as well. However, while their analyses primarily focus on firm performance through abnormal stock market returns, we use multiple measures of firm performance that range from sales, income, expenses, productivity, etc. Second, our results not only reinforce their conclusions, but also provide new insights into the mechanisms through which political connections enable firms to adjust their liabilities, borrowing, and asset portfolios in response to a macroeconomic crisis. In that sense, our paper is closest to Choi, Penciakova, and Saffie (2021), who examine how connected firms in the US are able to access government relief funds during hurricanes. Third, the richness of our data allows us to uncover various channels, such as the portfolio of short and long-term borrowings, assets, and liabilities, through which these connected firms perform better when faced with a crisis. Lastly, we innovate and capture political connections in a more comprehensive way by harnessing a newly developed sophisticated machine-learning method. Both data on political connections of Indian firms as well as the method for measuring political connections more precisely can be used in a wide array of applications and contexts beyond the one we study here.

Our paper also augments the literature on understanding the impact of demonetization on the Indian economy (Chodorow-Reich et al., 2020; Lahiri, 2020). While other studies examine its impact on households (Karmakar and Narayanan, 2020), agricultural markets (Aggarwal and Narayanan, 2021), consumer confidence (Mukhopadhyay, 2019), transmission through the supply chain (Kisat and Phan, 2020), as well its political economy (Banerjee and Kala, 2017; Bhavnani and Copelovitch, 2018; Khanna and Mukherjee, 2020). Fewer studies have examined the impact of this policy on changing firm operations and those that do (Crouzet et al., 2023; Das et al., 2023), have focused on the adoption of digital payments. To the best of our knowledge, this is the first study that shows the role of political connections in impacting firm outcomes after demonetization.

The rest of the paper is organized as follows. Section 2 provides a background of the empirical context, while Section 3 describes how we measure political connections. Section 4 describes the firm data in detail, while Section 5 describes our empirical strategy. Sections 6 and 7 present the empirical results on how political connections played a role during demonetization, and Section 8 conducts a number of robustness checks to rule out alternate explanations and increases our confidence in the results. Section 9 offers a short conclusion.

2. Demonetization in India

In a sudden and unexpected televised address to the nation on the evening of *November 8, 2016*, the Prime Minister of India announced that the two largest denomination notes—INR 500 ($7) and INR 1000 ($15), would cease to be legal tender at midnight and would be replaced by new INR 500 and INR 2000 rupee notes instead. These old notes, accounting for 86% of the pre-demonetization currency, could be deposited in banks before December 31, 2016, in exchange for new ones, but could not be used for any monetary transactions. The intended objective of this exercise, as emphasized by the Prime Minister, was to curtail corruption and eradicate black money and counterfeit currency notes from the economy. To maintain the secrecy of this policy, the Reserve Bank of India did not print and distribute a large quantity of these new notes, which unsurprisingly led to severe shortages and delays in replacing the old notes with new ones. This caused a lot of chaos and as shown in Fig. 1, the total currency declined by 75% overnight and recovered very slowly after that over the course of the next year (Chodorow-Reich et al., 2020; Lahiri, 2020).

While the government was able to recover 99% of the demonetized currency, the episode had an adverse impact on a cash-dependent Indian economy.[11] Estimates suggest a 3-4 p.p. decline in output and employment and a 2 p.p. decline in growth in the quarter of demonetization. Moreover, despite a large increase in bank deposits, bank lending remained constrained and while the currency in circulation recovered over the next year, economic recovery was slow even a couple of years after (Chodorow-Reich et al., 2020; Karmakar and Narayanan, 2020; Lahiri, 2020). This episode was a sharp, unexpected change in the economic conditions, resulting in a significant economic downturn and a severe cash crisis.

[10] This mitigates concerns around politically connected firms appointing certain types of Directors on their Board (who might be more connected themselves, for example) to deal with adverse economic situations. In fact, we show that it is not so much about connections in general, but specifically political connections that drive the results.

[11] Currency outside banks as a share of GDP was 12.5% in 2015 for India, as compared to 7.4% in the U.S. and 9.3% in China (Rogoff, 2016).

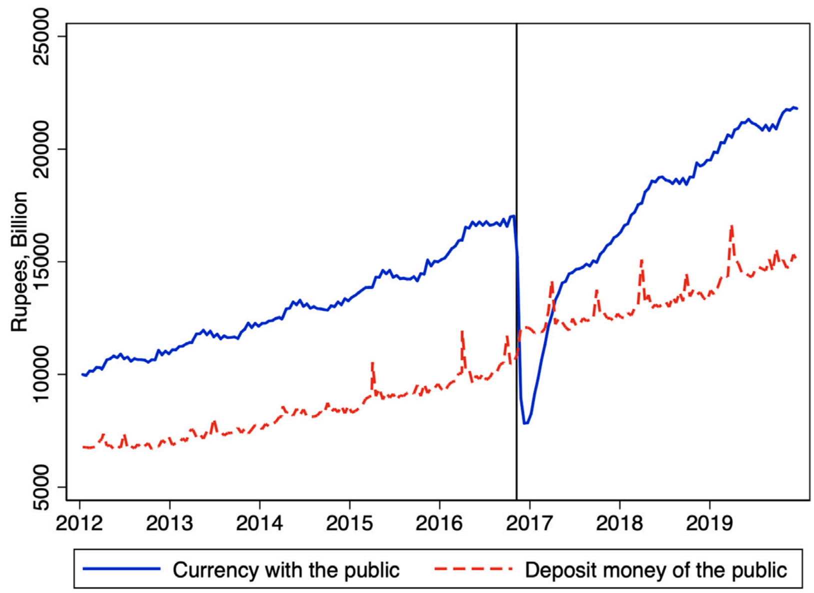


Fig. 1. Steep fall in cash
Notes: Data is from the Database on the Indian Economy published by the Reserve Bank of India. The units are in billions of Rupees and the frequency is fortnightly. The graph shows the time series of currency with the public (the blue solid line) and deposit money of the public (the red dashed line). Currency with the public is the currency in circulation less cash held by banks. Deposit money of the public is the sum of demand deposits with the banks and other deposits with the RBI. The black solid line is November 8, 2016. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3. Innovation in measuring political connections

3.1. Political connections measurements in existing literature

Previous literature has used a variety of ways to define political connections. In Appendix Section B, we list the various ways that political connections have been measured in the literature (Table B1). In highly cited studies, connections with some principal politicians have been leveraged. For example, Fisman (2001) identifies connections based on the Suharto Dependency Index, developed by the Castle Group, a leading economic consultant in Indonesia. The index ranges from one (least dependent) to five (most dependent). Companies affiliated with Suharto's children or allies have a high index. Likewise, Mobarak and Purbasari (2006) use connections to President Suharto. Khwaja and Mian (2005) consider a firm politically connected if its directors contest elections. A number of papers (Agrawal and Knoeber, 2001; Boubakri et al., 2012; Amore and Bennedsen, 2013; Bertrand et al., 2018) use politician CEOs and/or directors as the definition of political connection. Some papers (Claessens et al., 2008; Brown and Huang, 2020; Choi et al., 2021) use campaign contributions for measurement. Faccio (2006) advances the measurement of political connections significantly. Apart from being a politician, a former head of a state, a foreign politician, or a member of a political party, they consider whether a firm's top officers are "closely related" to a politician through relations, friendships, etc.

3.2. Our measure and its innovation

We now discuss how we create our measure of firms' political connections. This measure taps into various datasets and uses sophisticated machine-learning algorithms to link them together. Moreover, while we consider the Indian setting for this paper, the technique we demonstrate can be used more generally for other settings as well, with technical details on the data organization and the algorithm discussed in Sen et al. (2018).

Measuring political connections

First, we collate a comprehensive dataset of: (i) around 20,000 politicians who have held political office and/or contested in national and state elections from 2004 onwards[12]; (ii) universe of more than 11,000 retired and current bureaucrats in the Indian Administrative Services across all State and Central Government departments and ministries since 1961. Second, we collect information on the universe of around 65,000 Directors on the Board of publicly listed companies on the National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) from 1980 onwards. Since these Directors could be members of multiple Boards, we complement it with information on all subsidiaries of these firms, and the universe of firms registered with the Ministry of Corporate Affairs from 1980 onwards. Third, we then train ML algorithms to identify relatives, friends, and social contacts of these individuals from over 5 million news articles (crawled daily) from seven leading media outlets in India: *The Hindu, The Times of India, Indian Express, The New Indian Express, Telegraph, Deccan Herald,* and *Hindustan Times* between 2011 and 2016. We augment this by crawling Wikipedia pages as well as curating interviews, announcements, and appearances at personal and professional events. An entity resolution algorithm (see Sen et al. (2018) for the technical details) is then used to merge information on connections from different sources. Lastly, we determine if any politician, bureaucrat, or their kin and *social network* served as a Director for any of the firms described above, using a network graph (for up to 3 nodes) of kinship, interactions, and friendships between various entities (bureaucrats, politicians, their kin, and social network).

Example of a politically connected firm

We provide an example to highlight the intuition behind this method. From a news article published by the *Indian Express* (a large

[12] A ruling by the Supreme Court in November 2003 around citizens' Right to Information mandated all candidates contesting for public office to disclose information on assets and criminal records. We used these records and also leveraged information on www.indiavote.com www.persmin.gov.in.

NCP chief Sharad Pawar today exercised his franchise in a municipal ward where nine candidates are contesting and none of them belongs to NCP. Pawar, along with son-in-law Sadanand Sule and grand daughter Revati, voted here at a polling booth in ward no. 214, which comprises landmarks like the Mahalaxmi Mandir, Jaslok Hospital and the historic Gowalia Tank ground. There are nine candidates contesting from ward 214 in the Brihanmumbai Municipal Corporation elections, including those from Congress, Maharashtra Navnirman Sena and Shiv Sena.

(a) The Indian Express: Mr. Sharad Pawar & Mr. Sadanand Sule

View Director Master Data

DIN 00622248
Name SADANAND BHALCHANDRA SULE

List of Companies

CIN/FCRN	Company Name	Begin Date	End Date	ACTIVE compliance
U45200MH2005PTC150876	LAGUNA DEVELOPERS PRIVATE LIMITED	09/01/2008	-	ACTIVE compliant
U51100MH1997PTC105353	MIRACLE AGRO PRODUCTS PRIVATE LIMITED	15/09/2014	-	ACTIVE compliant
U63030MH2012PTC235832	COLDMAN LOGISTICS PRIVATE LIMITED	17/09/2012	-	ACTIVE compliant
U63030PN2011PTC138569	AARVEE COLD CHAIN LOGISTICS PRIVATE LIMITED	30/09/2014	-	ACTIVE compliant
U63043MH1999PTC120794	TRAVEL MASTERS (MUMBAI) PRIVATE LIMITED	14/07/1999	-	ACTIVE compliant
U63090MH2010PTC208719	TM HOLIDAYS PRIVATE LIMITED	07/10/2010	-	
U65944MH1991PTC064565	NISHANT FINANCE AND TRADING P LTD	07/09/2007	-	ACTIVE compliant
U65990MH1994PTC077431	RADIANT TRADEVEST PRIVATE LIMITED	22/10/1996	-	ACTIVE compliant
U70100MH2003PTC139307	VRS DEVELOPERS PRIVATE LIMITED	21/02/2003	-	ACTIVE compliant
U70102MH2007PTC171204	AARVEE REALTORS PRIVATE LIMITED	29/05/2007	-	ACTIVE compliant

(b) List of Firms where Mr. Sadanand Sule is a Director

Fig. 2. Politically connected firms: An example.

national daily) in 2017 (Fig. 2(a)), we establish that Mr. Sadanand Sule is the son-in-law of prominent politician Mr. Sharad Pawar. We also locate Mr. Sule from the Master Data of Directors maintained by the Ministry of Corporate Affairs and hence obtain the list of companies where Mr. Sule currently serves (or has ever served) as a Director. Fig. 2(b) displays this information. As shown, we know both a company's name and its unique Corporate Identification Number (CIN). These firms are then tagged as "politically connected" and the CIN is used to match them to the data on firms' outcomes described in Section 4 below.

3.3. Comparison with the literature benchmark of name matching algorithms

Our machine-learning algorithm (ML Algorithm) improves on other commonly used measures in the literature (such as proximity by social groups, regions, identity, etc.) as discussed previously, by combining machine-learning techniques to measure friendships, meetings, and social appearances reported in the media, which are usually difficult to measure and quantify. In other words, it uses "context-based matching" to define connections, in addition to "string-based matching" alone. This helps us avoid both Type I (false positives) and Type II errors (false negatives). In addition to this, context-based matching allows us to identify connections that would not have been possible to identify with string-based matching alone. Our method could be applied to any country or setting more generally.

To set a benchmark, we compare political connections identified by our ML algorithm with a name-matching algorithm (NM Algorithm) that is common in the literature. Of the approximately 31,500 firms in our sample (see Section 4.2 for more details), the NM algorithm classifies 9020 firms (or 28.6%) to be politically connected. On the other hand, the ML algorithm only identifies 867 political connections (2.7%). One reason, as noted earlier, is that while several names seemingly match, they are not necessarily the same people (false positives), while others whose names are mentioned differently in different sources might get missed (false negatives).[13] Looking at the overlap between the ML and NM samples, the ML algorithm classifies 757 of the 9020 firms identified by the NM algorithm (8.4%) as politically

[13] Here, we provide two examples: first, is Mr. Naveen Kumar, who is both a politician and a Director in 29 firms, but they are not the same person. However, the NM Algorithm incorrectly classifies these 29 firms to be politically connected. Second, Mr. H. K. Khan, who is a retired bureaucrat but also the same person as Mr. Hamidullah Kabir Khan, a Director of 7 firms. Due to low similarity scores in the NM matching exercise, these connections are missed.

connected.[14] The remaining 110 firms (around 13% of the final ML sample) could not have been detected by the NM algorithm alone and are detected using contextual information. While we work in a different context and setting, it is reassuring to note a similar order of magnitude difference in the literature as well | between the 25% politically connected firms that Khwaja and Mian (2005) find using NM exercises, as opposed to the 2.8% politically connected ones that Faccio (2006) find through name and context-based matching. In Appendix Section C.3, we redo our analysis and find that while politically connected firms identified through the NM Algorithm do perform better after the crisis (as opposed to non-connected ones), the quantitative magnitude is much smaller (potentially due to imprecise classification) as compared to politically connected firms identified through the ML approach.

4. Data

4.1. Data on firm outcomes

Data on firm outcomes is obtained from the Prowess Data of the Centre for Monitoring of the Indian Economy (CMIE). Prowess is a database of over 40,000 firms that includes all firms traded on the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE), and thousands of unlisted Public and Private Limited Companies. Data on these firms is collated and harmonized from Annual Reports, Quarterly Financial Statements, Stock Exchange feeds, and other publicly available sources. Appendix Section C.1 provides details on the selection and coverage of these firms. While the Prowess covers large registered firms in India's formal sector, it provides granular data on a large set of economic and financial outcomes of a firm. For example, the data provides information not only on output, income, capital, and labor but also on the portfolio of assets, liabilities, and borrowings. The data is a panel of firms going back to 1989 (though the coverage has improved significantly over time). Of particular relevance for this study is that the Prowess contains information on the CIN of a firm (that is unique to a firm) and information on the Board of Directors that includes their names and Director Identification Number (DIN). Both the CIN and DIN are provided by the Ministry of Corporate Affairs and are unique to a firm and Director. We use them to match the Prowess firms with the data on their political connections.

Lastly, while the Annual Survey of Industries (ASI) and the Prowess data are the most commonly used data on firms in India, we prefer using the Prowess primarily because the ASI does not provide information on the Board of Directors of a firm, making it impossible to measure its political connections. Moreover, unlike the Prowess, the ASI has limited information on firm assets and liabilities, which are particularly useful in our context to study the mechanisms underlying how politically connected firms systematically differ in their responses as compared to non-connected ones. Lastly, like the ASI, the Prowess is limited in its coverage since it collects data only on formal sector firms.

4.2. Sample characteristics

Our final sample consists of 31,492 firms that we observe from 2012–2019.[15] For each firm in our sample, we define a time-invariant dummy variable that takes the value 1 if the firm is politically connected before 2016 (based on the details in Section 3) and 0 otherwise. 867 firms in our sample (2.75%) are politically connected. This is similar in magnitude to Faccio (2006, 2010), who use a similar definition and find that on average 2.8% of firms in their sample spanning 47 countries, and 3.1% in India are politically connected.[16]

Across sectors, financial services (17.5%), electricity, gas, steam, and air conditioning supply (9.11%), wholesale trade (8.4%), warehousing and transportation (4.7%), and chemicals and chemical products (4.7%) are the five industries with the largest share of politically connected firms (44.5%) (Table C2). Table 1 summarizes basic characteristics and differences between politically connected and non-connected firms between 2012–2015 i.e., before demonetization. Section A in the Appendix provides detailed definitions for all the variables used in the analysis. As is clear from the table, connected firms are larger than non-connected firms in terms of their size (employees and capital stock), assets and liabilities, income, sales, and expenses. These patterns are very consistent with Faccio (2010), who study the differences in politically connected and non-connected firms across 47 countries.

5. Empirical strategy

As is clear from the previous section, political connections are not randomly allocated across firms (i.e., politically connected firms systematically differ from their non-connected counterparts). For example, even in the pre-period (before 2016), connected firms are larger and more productive than non-connected ones. One may thus be concerned about separately identifying the role of political connections from the role of unobserved firm characteristics in understanding how they respond to a macroeconomic shock. Our identification strategy mitigates these concerns.

All our empirical specifications include a firm fixed effect that controls for all observable and unobservable time-invariant *level* differences across connected and non-connected firms (such as entrepreneurial ability for example). However, time-varying differences (such as pre-period trends) are not captured. Therefore, we employ a Synthetic Difference-in-Differences (SDID) method (Arkhangelsky et al., 2021). The SDID method uses identification strategies from both the difference-in-differences (DID) as well as synthetic controls (SC) methods.

For example, DID permits time-invariant level differences (as well as general common trends) across units, thus drawing causal inferences based on the parallel trend assumption i.e., in the absence of treatment, treated units would have followed parallel paths to non-treated units.[17] Another approach, given the challenge of meeting this strong parallel trends assumption has been to implement synthetic control (SC) methods. SC seeks to generate a single synthetic control unit from optimally weighted underlying control units such that it closely matches pre-treatment outcomes of treated units as much as possible (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015). SDID seeks to bridge the DID and SC procedures by: (i) re-weighting and matching pre-exposure trends on the outcome variables; and (ii) allowing for additive unit and time-specific selection into the treatment, thus allowing for valid large-panel inference which is similar to DID (Arkhangelsky et al., 2021). Therefore, like DID models, SDID allows for treated and control units

[14] This is perhaps intuitive in the Indian context since there are complex rules, requirements, and laws that govern how bureaucrats and politicians can hold an "office-of-profit", such as being a Director in a firm.

[15] While our results are robust to including previous years (2010 onwards) as well, the impact of the global financial crisis in 2008, large industrial policy reforms implemented in India in 2005–2006, and their aftermath could systematically differ based on political connections of a firm, affecting our interpretation of the pre-period. We, therefore, restrict our panel from 2012 onwards. We end our panel in 2019 to avoid contaminating the post-period with the impact of COVID-19 in India starting March 2020.

[16] Of these politically connected firms, 95% are connected through bureaucrats, with the rest connected through politicians. Moreover, 13% of connections are identified through the context-based approach that would have been completely missed in a standard name-matching algorithm commonly used in the literature.

[17] Recently, a number of methodologies have sought to loosen this assumption, which includes partial identification (Rambachan and Roth, 2023), and flexible procedures to adequately control for any pre-treatment differences across units (Goodman-Bacon, 2021; Bhuller et al., 2013).

Table 2
Impacts on Income, Sales, Expenses and TFPR.

	Ln(Income)	Ln(Sales)	Ln(Expenses)	Ln(TFPR1)	Ln(TFPR2)
	(1)	(2)	(3)	(4)	(5)
Connected × Post	0.118***	0.087***	0.119***	0.053***	0.050***
	(0.027)	(0.030)	(0.029)	(0.020)	(0.019)
Control Mean	2.32	2.14	2.35	0.85	0.70
R^2	0.95	0.96	0.96	0.88	0.94
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes	Yes
No. of firms	31,333	31,333	31,333	28,622	28,622
N	186,937	186,937	186,937	161,777	161,777

Notes: Income in Column (1) is the sum of all kinds of income an enterprise generates during an accounting period. Sales in Column (2) are all regular income generated by companies from the clearly identifiable sales of goods and from non-financial services. Expenses in Column (3) are the sum of all revenue expenses incurred by a company during an accounting period. TFPR in Columns (4) and (5) are a firm's Total Factor Revenue Productivity calculated based on the method proposed by Levinsohn and Petrin (2003). In Column (4), the free variables are compensation to employees and raw material expenses and the proxy variable is power, fuel, and water charges; in Column (5), the free variable is compensation to employees and the proxy variable is the consumption of raw material and power, fuel, and water. Section A in the Appendix provides the definition for all variables in detail. We use the log inverse hyperbolic sine transformations for all variables. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

to be trending on entirely different levels prior to a reform of interest; and like SC methods, optimally generates a matched control unit which considerably loosens the need for parallel trend assumptions. Correspondingly, SDID avoids common pitfalls in standard DID and SC methods – namely an inability to estimate causal relationships if parallel trends are not met in aggregate data, and a requirement that the treated unit be housed within a "convex hull" of control units in the case of SC.

In our setting therefore, SDID allows us to mitigate concerns that the *selection* of firms who acquire political connections (like those with higher entrepreneurial ability, better resilience, etc.) rather than the political connections themselves can explain how they respond to a macroeconomic shock.[18] We use the unit weights and time weights derived from SDID to re-weight our panel data in the regressions.[19] For a firm i (in industry j and district d) in year t, we then estimate the following regression specifications:

$$Y_{it} = \alpha_i + \alpha_{dt} + \alpha_{jt} + \sum_{t=2012}^{2019} \beta_t \quad Connected_i \times 1(Year = t) + \gamma X_{it} + \varepsilon_{it} \qquad (1)$$

$$Y_{it} = \alpha_i + \alpha_{dt} + \alpha_{jt} + \beta \quad Connected_i \times Post_t + \gamma X_{it} + \varepsilon_{it} \qquad (2)$$

where Y_{it} are a set of outcome variables of a firm i in year t (such as sales, income, expenditure, etc.). Connected$_i$ is a time-invariant definition that takes the value 1 if a firm was ever politically connected in the pre-period, and 0 otherwise. Eq. (1) is a standard event-study design where $1(Year = t)$ takes the value 1 in year t and 0 otherwise. We take 2015 (the year before demonetization) as the base year. In Eq. (2), we pool the pre and post-policy years together and define a variable Post$_t$ that takes the value 1 for the years 2016–2019 and 0 otherwise. α_i are firm fixed effects that control for all observed and unobserved time-invariant characteristics of a firm, including those that allow them to become politically connected in the first place. α_{dt} and α_{jt} are district×year and industry×year fixed effects. These control for all characteristics of districts and industries over time that could influence the outcomes of a firm and be correlated with the demonetization shock, such as aggregate changes at the district level (price and wage changes) as well as industry-specific impacts of the shock over time.[20] Lastly, we cluster standard errors at the district level for statistical inference. In Appendix Section H.8, we show that our inference does not change when we cluster standard errors at the firm level instead.

6. Results

6.1. Impact on firm income, sales, and expenses

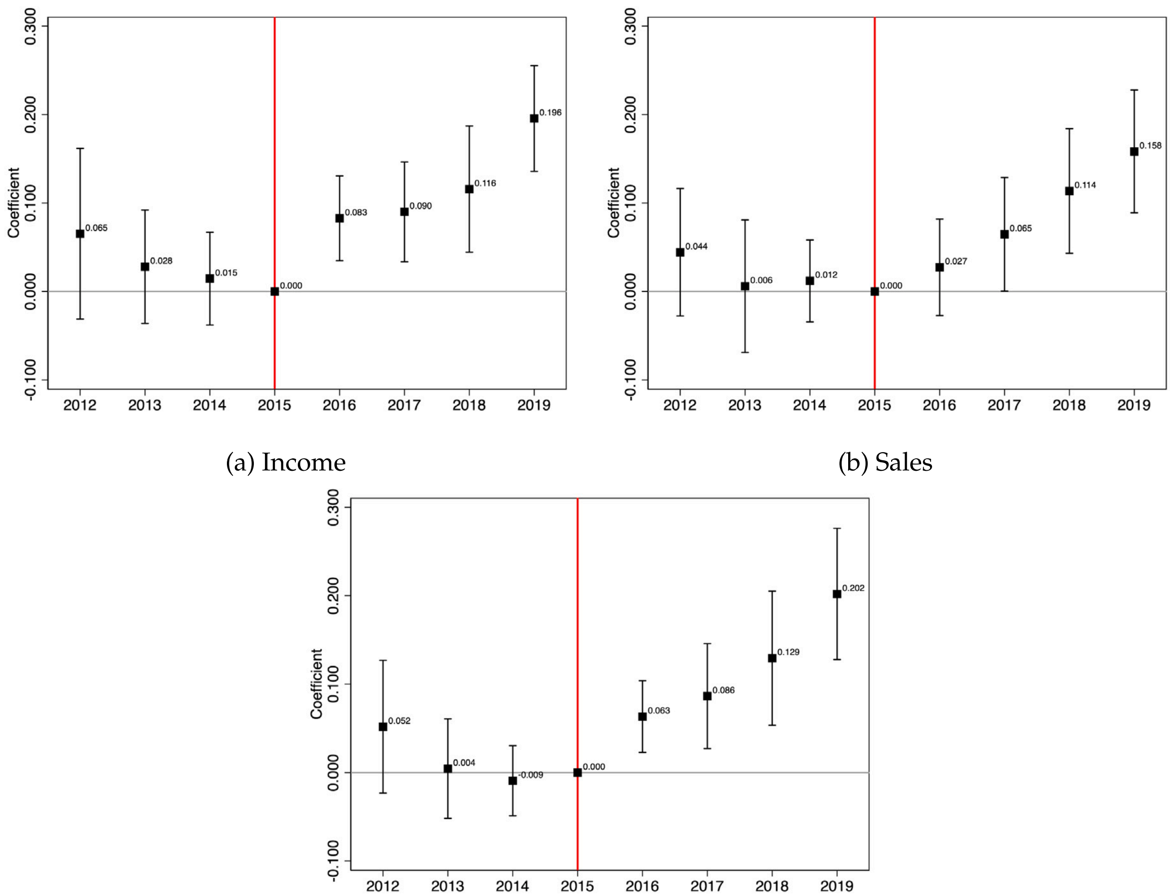
We begin by examining the impact of demonetization on the income, sales, and expenses of firms. Appendix Section A provides definitions of all the firm variables that are used in our analysis. We take the log inverse hyperbolic sine transformations of these variables to be able to include zeros, where applicable. The estimated coefficients $\hat{\beta}_t$ from the event-study specification (Eq. (1)) are reported in Fig. 3. By construction, there is no difference in income, sales, and expenses between politically connected firms and their (synthetic) non-connected counterparts before demonetization. Both the estimated coefficients are small, and they are statistically insignificant at conventional levels. However, we see a substantial difference between the two groups after demonetization, which is both increasing and persistent over the three years that follow. Politically connected firms report approximately 8–20 log-points (8.7–21.7%) higher income, 3–15 log-points (2.7–16.9%) higher sales, and 6–20 log-points (6.5–22.4%) higher expenses compared to their non-connected counterparts. Table 2 then reports these effects in a standard difference-in-differences specification (Eq. (2)). From Columns (1)–(3), politically connected firms have around 8.7–11.9 log-points (9.1–12.6%) higher income, sales, and expenses relative to the non-connected firms.

Given the difference-in-differences specification, our estimates capture the changes reported by politically connected firms *relative* to non-connected ones. Therefore, it is unclear just from these estimates whether firm outcomes (sales, for example) recovered quickly after the crisis, or actually grew when compared to the pre-crisis period. This is particularly important when we (in subsequent sections) examine changes in firms' assets and investments and the resulting changes in productivity and TFP. In Figures D1 and D2, we report the trends in sales for connected and non-connected firms respectively. These figures show two patterns: first, the decline in sales was lower for connected

[18] In addition to this identification strategy, Section 8 provides multiple tests and additional analyses to rule out alternate explanations and increase confidence in the causal interpretation of our findings.

[19] For calculating the weights, we use an R package developed by Arkhangelsky et al. (2021), and match firms on the outcome variables while controlling for their age, whether the firm is listed on the stock market or not, log of value of total transactions on BSE or NSE, and log of value-add tax. SDID requires strongly balanced data. We, therefore, assign a small weight to observations that are not used in SDID but show that the results are robust enough to relax this requirement later in the paper.

[20] India introduced the Goods and Services Tax (GST) in 2017, which varied across products and industries. Therefore, in addition to controlling for industry×year fixed effects, we also control for the amount of GST tax paid by a firm as well.



(a) Income

(b) Sales

(c) Expenses

Fig. 3. Event study graphs: Impact on income, sales, and expenses of firms.
Notes: The above graphs plot the regression coefficients from Eq. (1) and estimate the relative difference between connected and non-connected firms for a set of outcome variables. 2015, the year before demonetization, is taken to be the base year. Section A in the Appendix provides detailed descriptions of all outcome variables. We use log inverse hyperbolic sine transformations for all outcome variables. All regressions include firm, district-year, and industry-year fixed effects, as well as control for the log of Goods and Service Tax payments. Each observation is weighted using weights calculated in the SDID. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

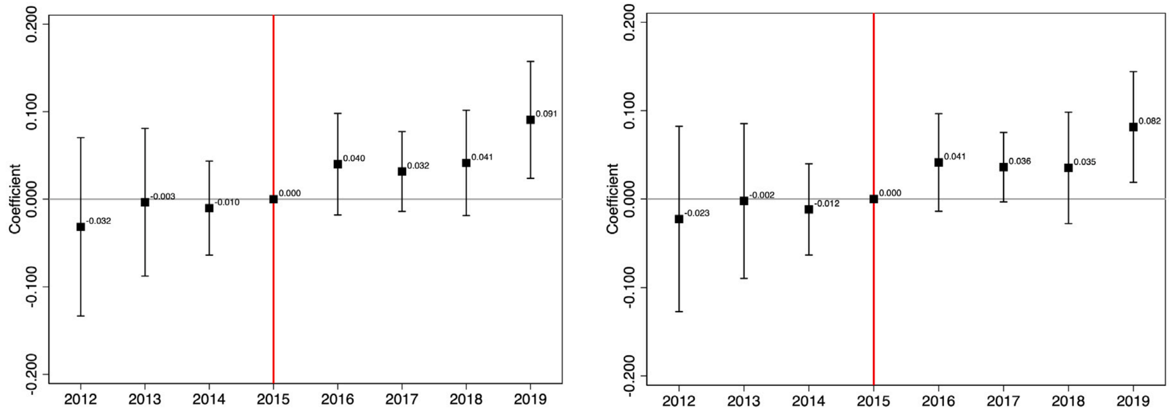
firms as compared to non-connected ones i.e., they were more robust to the crisis; and second, both connected and non-connected firms experienced a growth in sales after the crisis, but growth was much faster for connected firms i.e., these firms were more resilient as well (Khanna et al., 2022).

6.2. Impact on firm productivity

We now turn to examine whether the demonetization shock differentially affected firm productivity. A long panel of firms in our data allows us to construct a commonly used measure of productivity in the literature, namely: Revenue Total Factor Productivity or TFPR. Specifically, we construct two measures of TFPR for a firm using the method proposed by Levinsohn and Petrin (2003).[21] For the first measure (denoted by TFPR1), we use the wage bill and raw material expenses as free variables with expenditure on power, fuel, and water as a proxy variable. For the second measure (denoted by TFPR2), we use the wage bill as a free variable and the consumption of raw material expenses and expenditure on power, fuel, and water as a proxy variable instead. As reported in Table 1, politically connected firms have around 11–20 log-points (11.7%–22.7%) *higher* TFPR as compared to non-connected ones in the pre-period. Similar to the event study results discussed previously, we see that after demonetization, connected firms exhibit a 3%–9% higher increase in their TFPR as compared to non-connected ones (Fig. 4). Consequently, as reported in Columns (4) and (5) of Table 2, this translates into connected firms having an average of 5.2%–5.4% higher TFPR relative to their non-connected counterparts after demonetization. While the magnitude of these coefficients is non-trivial, Fig. 4 suggests a potential lag in firms' ability to improve their capabilities.

A large literature discusses the source of these productivity gains (TFPR), predominantly along three dimensions: (i) gains in the quantity efficiency as measured by TFPQ (De Loecker, 2011; Katayama et al., 2009); (ii) price markups; (iii) change in firm capability as measured by product quality and scope. Using tailored primary surveys of firms, Atkin, Khandelwal, and Osman (2019) show that TFPR is actually a better proxy for measuring the broader capabilities of firms as opposed to TFPQ. This is because the measurement of TFPQ requires observing prices directly across all products within a firm and then adjusting it for the quality and specification of these products. Both of these are challenging in standard administrative data (like ours) and

[21] The Levinsohn–Petrin approach uses expenditure on intermediate inputs of firms as a proxy for the free variables. In general, we use income, fixed assets, compensation to employees, raw material expenses, and expenditure on power, fuel, and water for the estimation of the production function, along with a package developed by Rovigatti and Mollisi (2018) that allows us to incorporate systematic firm attrition as well. It should be noted, however, that the Prowess is not well suited for understanding firm entry and exit because it is not mandatory for firms to report their status to the data collecting agency.



(a) TFPR1 (b) TFPR2

Fig. 4. Event study graphs: Impact on TFPR of firms.
Notes: The above graphs plot the regression coefficients from Eq. (1) and estimate the relative difference between connected and non-connected firms for a set of outcome variables. 2015, the year before demonetization, is taken to be the base year. Figures (a) and (b) use TFPR estimated by the method of Levinsohn and Petrin (2003). The free variables are compensation to employees and raw material expenses, and the proxy variable is power, fuel, and water charges in Fig. 4(a). The free variable is compensation to employees, and the proxy variable is the consumption of raw material and power, fuel, and water in Fig. 4(b). Section A in the Appendix provides detailed descriptions of all outcome variables. We use log inverse hyperbolic sine transformations for all outcome variables. All regressions include firm, district-year, and industry-year fixed effects, as well as control for the log of Goods and Service Tax payments. Each observation is weighted using weights calculated in the SDID. Standard errors are clustered at the district level. Confidence intervals are at the 95 percent level.

can lead to TFPQ being a poor proxy of a firm's capabilities. Moreover, if firms' capabilities come from their ability to produce both quality and quantity, TFPR may indeed be the primary object of interest.

Nevertheless, we try to make progress in measuring the sources of these TFPR gains to the extent possible in our setting. First, we do not observe prices directly for each product across all firms in our sample. However, we do observe the quantity and value of sales for each product for around a third of the firms in our sample, mostly operating in the agriculture and manufacturing sectors. While on the one hand, it allows us to examine TFPQ changes for these firms, it presents additional challenges in measurement and inference (in line with the previous discussion). We discuss these in detail in Appendix Section E and follow Bau and Matray (2023), who use the same data, to construct TFPQ measures. We find no differential improvement in TFPQ for politically connected firms relative to their non-connected counterparts after demonetization (Table E1).

Turning to the other sources of TFPR changes, Kisat and Phan (2020) document that adjustment in markups was an important channel in explaining firm responses to the shock after demonetization, though given the data limitations, we are unable to examine differentially for connected and non-connected firms. In line with Atkin et al. (2019), however, we find that politically connected firms (as compared to non-connected ones) expand their product scope after the shock (Column 5 of Table E1).[22]

Put together, the above analysis suggests that politically connected firms, as compared to their non-connected counterparts, may have enhanced their capabilities after demonetization, as measured by a higher TFPR and wider scope of products, with no discernible difference in TFPQ.

7. How do political connections matter?

With detailed data on the portfolio of assets and liabilities, we now turn our attention to examining the mechanisms through which politically connected firms perform better as compared to their non-connected counterparts. Section 7.1 discusses firm borrowings and access to credit, including those from banks and the public sector. Sections 7.2 and 7.3 then discuss changes in firm liabilities and assets. Given the economic downturn, Section 7.4 examines whether politically connected firms were differentially able to acquire other firms. Finally, Section 7.5 offers a short discussion to synthesize these results. We define all variables in detail in Appendix Section A. While we report the results from the SDID specification (Eq. (2)), the associated event-study graphs from Eq. (1) for borrowings, liabilities, and assets are reported in Appendix Section J.

7.1. Firm borrowings

A large literature has documented how firms use their political connections to get access to credit. However, the channels through which these firms obtain the credit are not as well documented. Given the rich data, we begin by examining how politically connected firms (relative to non-connected ones) changed the composition of their borrowings. Specifically, we examine changes along four dimensions: (i) short-term and long-term borrowings; (ii) secured and unsecured borrowings; (iii) borrowings from banks; and (iv) borrowings from state and central governments.

Short-term and long-term borrowings. In Panel A of Table 3, we find that the total borrowings of connected firms are approximately 4.9 log-points (5%) lower as compared to their non-connected counterparts (Column 1). However, there is a distinct shift in the nature of their borrowings | connected firms decrease long-term borrowings (expected to be repaid beyond a year) for a potential increase in short-term borrowing (expected to be paid within a year). In particular, long-term borrowings decrease by around 14.1 log-points (15.1%, Column 3), while short-term ones increase by around 6.3 log-points (6.5%, Column 2), though this is not statistically significant at conventional levels. The share of short-term borrowings increases by 2.8 p.p. or 5% (Column 4). In order to shed light on the relevance of these results, we explore the portfolio of borrowing, especially from banks and the government.

[22] Goldberg, Khandelwal, Pavcnik, and Topalova (2010) show that multi-product firms, for example, tend to have a higher TFP compared to single-product firms.

Table 3
Impacts on the Portfolio of Borrowings.

	(1)	(2)	(3)	(4)
Panel A. Long and Short-term Borrowings				
	Ln(Total Borrowings)	Ln(Short-Term Borrowings)	Ln(Long-Term Borrowings)	Short-Term/Total
Connected × Post	−0.049+	0.063	−0.141***	0.028**
	(0.033)	(0.052)	(0.051)	(0.012)
Control Mean	2.13	1.48	1.31	0.56
R^2	0.95	0.89	0.92	0.82
Panel B. Secured and Unsecured Borrowings				
	Ln(Total Borrowings)	Ln(Secured Borrowings)	Ln(Unsecured Borrowings)	Unsecured/Total
Connected × Post	−0.049+	−0.085***	0.047	0.009
	(0.033)	(0.028)	(0.065)	(0.011)
Control Mean	2.13	1.81	0.86	0.25
R^2	0.95	0.93	0.83	0.73
Panel C. Borrowings from Banks				
	Ln(Total Bank Borrowings)	Ln(Short-Term Bank Borr.)	Ln(Long-Term Bank Borr.)	Short-Term/Total
Connected × Post	−0.087***	0.032	−0.090*	0.025***
	(0.028)	(0.043)	(0.047)	(0.010)
Control Mean	1.73	1.21	0.92	0.63
R^2	0.92	0.89	0.90	0.80
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
No. of firms	19,536	19,536	19,536	19,536
N	103,838	103,838	103,838	103,838

Notes: Short-term Borrowings (Column 2, Panel A) are those that have to be repaid within a year whereas Long-term Borrowings (Column 3, Panel A) do not have to be repaid within a year. Secured Borrowings (Column 2, Panel B) are those where the borrower pledges some assets with the lender as collateral and in case of default, the lender has the authority to sell the pledged assets and recover the due. Short-Term Bank Borrowings (Column 2, Panel C) are those borrowings taken from a bank and have to be repaid within a year. Long-Term Bank Borrowings (Column 3, Panel C) do not have to be repaid within a year. Section A in the Appendix provides the definition for all variables in detail. We use the log inverse hyperbolic sine transformations for all variables. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Secured and unsecured borrowings. An important dimension of firm borrowings, especially through formal channels (such as banks) is whether they are secured or unsecured borrowings. The primary difference between them is that secured borrowings are made on the security of an asset whose market value is no less than the borrowing amount (collateral for example). On the other hand, unsecured borrowings require no such collateral, but usually also attract higher interest rates. As reported in Panel B of Table 3, connected firms (as compared to their non-connected counterparts) shifted their portfolio away from secured borrowings (Column 2) and towards unsecured borrowings (Column 3). Connected firms (as compared to non-connected ones) decreased their secured borrowing by around 8.5 log-points (8.8%) and increased unsecured borrowings by around 4.7 log-points (4.8%). The latter, though large in magnitude, is not statistically significant at conventional levels.

Firm borrowings from banks. Bank borrowings of firms are of specific interest given the nature of the demonetization episode, which severely affected the cash holdings and lending capacity of banks. Figure F1a in the Appendix uses quarterly data from the Reserve Bank of India to plot the total value of loans issued by all scheduled commercial banks of India. As is clear from the figure, bank loans were not severely impacted after demonetization.[23] However, from Figure F1b, the composition of these loans changed–banks were more likely to issue long-term loans as opposed to short-term ones i.e., there was a small decline in the value of short-term loans as a fraction of total loans.[24] From Figure F2 however, these long-term loans were also issued at higher interest rates, thus increasing the long-term cost of firm borrowing. With this context, Panel C of Table 3 examines the borrowings of politically connected firms from banks, as compared to non-connected ones. In line with the higher (long-term) cost of borrowing, we see around an 8.7 log-points (9.1%) decline in total bank borrowings (Column 1), which is driven largely by around a 9 log-point (9.4%) decrease in long-term bank borrowings (Column 3). Therefore, short-term bank borrowings as a share of total bank borrowings increased by 2.5 p.p. (4%) for connected (relative to non-connected) firms (Column 4).

Firm borrowings from the government. While we cannot determine whether borrowings came from public or private sector banks, our data captures information on any borrowings that firms made from state and central governments. In Table 4, we analyze the differential response of politically connected firms regarding both the likelihood and the amount of borrowing. Specifically, Panel A shows that public sector borrowing by connected firms (relative to non-connected firms) increased by approximately 3.4 log-points (3.5%) after the crisis (Column 1), though this coefficient is statistically insignificant at conventional levels. However, as shown in Columns (2) and (3), this potential increase was driven entirely by short-term borrowings, which rose by about 4%, rather than long-term borrowings. Panels B and C further disaggregate these effects by the extensive margin i.e., the probability of borrowing (Panel B); and the intensive margin i.e., the amount borrowed, conditional on borrowing (Panel C). In Panel B, politically connected firms were 1.8 p.p. more likely to borrow from the government, with increases observed in the probability of both short-term (0.07 p.p.) and long-term borrowing (1.6 p.p.). On the intensive margin (Panel C), politically connected firms increased their total borrowings by around 20% (Column 1), driven entirely by an increase in short-term government borrowings (Column 2). Long-term borrowings by connected firms, if anything, decreased as compared to non-connected ones (Column 3, Panel C). It is worth noting that results

[23] This is consistent with Lahiri (2020), who documents no sharp changes in bank lending after demonetization, despite the substantial increase in bank deposits during this period.

[24] Refer to Section F for information on the source of the data and the methodology used to calculate the share of short-term loans over total loans.

Table 4
Impacts on the Portfolio of Government Borrowings.

	Ln(Total Borrowings)	Ln(Short-Term Borrowings)	Ln(Long-Term Borrowings)
	(1)	(2)	(3)
Panel A. Amount of Public Sector Borrowings			
Connected × Post	0.034	0.039**	0.017
	(0.031)	(0.020)	(0.040)
Control Mean	0.01	0.00	0.01
R^2	0.91	0.93	0.89
No. of firms	21,457	21,457	21,457
N	107,982	107,982	107,982
Panel B. Probability of Public Sector Borrowings (Extensive Margin)			
Connected × Post	0.018**	0.007+	0.016**
	(0.009)	(0.005)	(0.007)
Control Mean	0.01	0.00	0.01
R^2	0.89	0.93	0.86
No. of firms	21,457	21,457	21,457
N	107,982	107,982	107,982
Panel C. Amount of Public Sector Borrowings | Any Borrowings			
Connected × Post	0.195	0.259	−0.078
	(0.313)	(0.221)	(0.308)
Control Mean	0.52	0.11	0.44
R^2	0.93	0.98	0.93
No. of firms	363	363	363
N	1,990	1,990	1,990
Firm FE	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes

Notes: Column (1) reports the total borrowings from central and state governments. Short-term borrowings (those that have to be repaid within a year), and long-term borrowings (those that do not need to be repaid within a year) are reported in Columns (2) and (3) respectively. Panels A reports the total public sector borrowings, while Panels B and C split it on the extensive and intensive margins. Panel B defines a binary outcome variable that takes the value 1 if a firm has had any borrowings (Column 1), short- or long-term borrowings (Columns 2 and 3). Panel C uses the amount of borrowings conditional on any borrowings i.e., it drops the firms that have no borrowings from the government. We use the log inverse hyperbolic sine transformations of the outcome variables in Panels A and C. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is p < 0.15, * is p < 0.1, ** is p < 0.05, and *** is p < 0.01.

from Panel C are only suggestive, as the coefficients are imprecisely estimated and lack statistical significance at conventional levels due to limited statistical power from the small number of firms that borrow from the government.

Discussion. These results suggest that politically connected firms (as compared to non-connected ones) reduced their total borrowings but shifted the composition of their debt across loan duration (short vs. long), borrowing type (secured vs. unsecured), and borrowing source (banks vs. government). First, given the rise in interest rates following the demonetization shock (see Appendix Section F for details), connected firms were able to reduce their now-costlier long-term borrowings, particularly from banks, by substituting them with long-term loans from government sources instead. Second, connected firms more generally skewed their borrowings portfolio towards more short-term borrowings. In particular, they increased short-term borrowings from the government, with both the probability of short-term borrowing and the amount borrowed rising after the crisis. Lastly, connected firms were less inclined to take out collateralized, secure loans, in favor of more unsecured ones instead.

7.2. Firm liabilities

We now examine how politically connected firms differentially altered their liabilities, as compared to their non-connected counterparts, after demonetization. From Panel A in Table 5, politically connected firms (as compared to their non-connected counterparts) reported around a 5.5 log-points increase in their total liabilities (Column 1). We then examine whether these liabilities were driven by changes in short-term (Current) or long-term (Non-Current) liabilities. Current liabilities represent all liabilities or debts that a firm owes its suppliers, vendors, banks, etc., and must be paid within a year, while non-current liabilities are longer-term liabilities that are not expected to be settled within a year. From Columns (2)–(4), we find that the increase in total liabilities was driven by an 8.2 log-points increase in the current liabilities of a firm. Current liabilities as a fraction of the total liabilities also increased by 1.5 p.p. or 3.8% (Column 4), with no differential change in non-current (or longer-term) liabilities (Column 2).

Given this, we further explore various components of current liabilities in Panel B, namely: short-term borrowings (Column 1), payables (Column 2), advances (Column 3), and other liabilities (Column 4). Short-term payables are liabilities that a firm owes its suppliers, creditors, and lenders for purchases of goods and services that are expected to mature within a year. Short-term advances are deposits and advances taken from customers and employees, while other current liabilities constitute payment of maturities, debt, interest accrued, etc. From Panel B, politically connected firms (as compared to non-connected counterparts) reported around a 7% increase in the payments of their short-term payables (Column 2). The changes in short-term borrowings (Column 1) and advances (Column 3) on the other hand were smaller in magnitude (3%–4%) and statistically significant at conventional levels. Lastly, connected firms reported around an 11.8 log-points (12.5%) increase in their other current liabilities than their non-connected counterparts (Column 4). Put together, connected firms were able to increase their short-term liabilities, particularly what they owed their creditors and suppliers, as well as delay immediate debt and interest payments.

7.3. Firm assets

Given the changes in connected firms' liabilities and borrowings, we now turn to examine how they systematically altered their asset portfolio.

Table 5
Impacts on the Portfolio of Liabilities.

	(1)	(2)	(3)	(4)
Panel A. Current and Non-Current Liabilities				
	Ln(Total Liabilities)	Ln(Non-Current Liabilities)	Ln(Current Liabilities)	Current/Total
Connected × Post	0.055***	0.010	0.082***	0.015*
	(0.019)	(0.025)	(0.015)	(0.008)
Control Mean	2.79	1.19	1.79	0.40
R^2	0.98	0.93	0.94	0.83
Panel B. Components of Current Liabilities				
	Ln(Short-Term Borrowings)	Ln(Short-Term Payables)	Ln(Short-Term Advances)	Ln(Other Current Liabilities)
Connected × Post	0.042	0.067***	0.029	0.118***
	(0.036)	(0.023)	(0.021)	(0.026)
Control Mean	1.00	1.02	0.31	0.66
R^2	0.87	0.93	0.84	0.89
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
No. of firms	29,989	29,989	29,989	29,989
N	173,296	173,296	173,296	173,296

Notes: Current Liabilities of a firm are those liabilities or debts that must be paid within a year whereas Non-Current Liabilities are longer-term debts that need not be paid within a year. Short-Term Borrowings are those that have to be repaid within a year. Short-Term Payables are liabilities owed to suppliers, vendors, and creditors for goods and services received that will mature within a year. Short-Term Advances are deposits and advances received from customers and employees. Other current liabilities include current maturities of long-term debt and lease, interest accrued but not due (short term), and unclaimed and unpaid dividends. Section A in the Appendix provides the definition for all variables in detail. We use the log inverse hyperbolic sine transformations of the outcome variables. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

In Panel A of Table 6, we see that connected firms had around 4 log-points (4.1%) more assets as compared to non-connected firms after demonetization (Column 1), with around a 5 log-points (5.1%) and 6.4 log-points (6.6%) increase in their short-term (current) and long-term (non-current) assets respectively (Columns 2 and 3).[25] As noted in Column (4), the share of current (and hence non-current) assets as a fraction of total assets did not change.

In Panel B of Table 6, we then examine the different components of current assets, namely current (short-term) investments, inventories, bank balance, and other assets. Short-term investments of a firm are those that are expected to mature within a year. Current inventories are materials held to be consumed in the production process or for sale, while bank balances capture the deposits that a firm has in a bank. Other current assets include all other short-term assets held by a firm such as trade and bill receivables, assets held for sale and short-term transfer, etc. We find that connected firms reported a 5.3 log-points (5.4%) increase in short-term (current) investments (Column 1) as well as a 7.7 log-points (8%) increase in other current assets relative to their non-connected counterparts after demonetization. There was no differential change in short-term inventories and bank balances between these groups of firms (Columns 2 and 3).

In Panel C of Table 6, we also examine the components of non-current (long-term) assets. From Columns (1) and (2), we find that connected firms reported around a 9.3 log-points (9.7%) increase in their non-current investments (i.e., long-term investments) and 5 log-points (5.1%) higher expenditure on intangible goods (such as software, rights, etc.), as compared to their non-connected counterparts after demonetization. From Columns (3) and (4), we do not find any statistically significant difference in fixed assets (such as buildings, land, etc.) as well as expenditure on property, plant, and equipment.

[25] Current assets are defined as those assets that can be easily converted into cash within 12 months (for example, cash balances, short-term investments, and inventory, etc.). Non-current assets on the other hand include more long-term fixed assets and investments that cannot be liquidated within a year (for example, intangible and fixed assets, property, plant, and PPE equipment, etc.). See Appendix A for the definitions of these variables.

7.4. Mergers and acquisitions

Economic crises can present opportunities for more robust and resilient firms, such as those with political connections, to acquire firms in less advantageous positions. Therefore, we further examine whether politically connected firms were more likely to merge with other firms, acquire other firms, or get acquired by another one. We report the results in Table 7. First, note from the control means that mergers and acquisitions are very rare among these very large firms in India. This is consistent with a large literature on how inefficient corporate, labor, and bankruptcy laws prevent these from happening. Nevertheless, our results suggest that connected firms were no more likely than non-connected ones to either merge (Column 1) or get acquired (Column 3). However, these firms were 1.8 p.p. more likely to acquire another firm (Column 2), primarily driven by acquisitions in the year right after the crisis (see Appendix Figure J5b).

7.5. Discussion

The above analysis is helpful in uncovering key channels through which politically connected firms were able to increase their income, sales, expenses, and TFP relative to non-connected firms after demonetization, despite the fact that the demonetization resulted in a transitory economic downturn. First, politically connected firms cut down on more costly long-term borrowings (from banks) and shifted the composition of their borrowings towards more short-term, unsecured borrowings, from banks and the government. Second, politically connected firms were able to delay the payment of their short-term liabilities, and in particular, payments made to creditors and suppliers as well as short-term interest and debt payments. Lastly, there was a clear increase in the total assets held by politically connected firms (relative to non-connected ones). This increase was reported both for short and long-term investments of these firms, as well as investments in acquiring intangible assets (such as computer software, patents, marketing rights, etc.). Hence, our analysis sheds light on multiple channels through which connected firms were able to react to a macroeconomic shock by adjusting the composition of their assets, liabilities, and borrowings. Of special note is how these firms were able to get

Table 6
Impacts on the Portfolio of Assets.

	(1)	(2)	(3)	(4)
Panel A. Current and Non-Current Assets				
	Ln(Total Assets)	Ln(Non-Current Assets)	Ln(Current Assets)	Non-Current/Total
Connected × Post	0.040**	0.050*	0.064***	0.002
	(0.015)	(0.029)	(0.020)	(0.005)
Control Mean	2.66	1.84	2.02	0.44
R^2	0.98	0.97	0.96	0.88
Panel B. Components of Current Assets				
	Ln(Current Investments)	Ln(Current Inventories)	Ln(Bank Bal.)	Ln(Other Current Assets)
Connected × Post	0.053*	−0.005	−0.035	0.077**
	(0.028)	(0.023)	(0.025)	(0.031)
Control Mean	0.12	0.96	0.55	1.22
R^2	0.74	0.95	0.88	0.93
Panel C. Components of Non-Current Assets				
	Ln(Non-Current Investments)	Ln(Exptd. on Intangibles)	Ln(Exptd. on Fixed Assets)	Ln(Exptd. on PPE)
Connected × Post	0.093*	0.050***	0.018	−0.018
	(0.047)	(0.016)	(0.031)	(0.031)
Control Mean	0.48	0.09	1.27	1.23
R^2	0.92	0.84	0.96	0.96
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes	Yes
No. of firms	30,231	30,231	30,231	30,231
N	175,709	175,709	175,709	175,709

Notes: Current Assets (and their components) are those assets held by the firm that can be easily converted to cash by the firm within 12 months. Non-Current Assets (and their components) cannot be converted to cash within 12 months. Section A in the Appendix provides the definition for all variables in detail. We use the log inverse hyperbolic sine transformations of the outcome variables. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. + is $p < 0.15$, * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

Table 7
Impacts on Mergers and Acquisitions.

	Merge	Acquire	Acquired
	(1)	(2)	(3)
Connected × Post	−0.001	0.018***	−0.010
	(0.009)	(0.004)	(0.010)
Firm FE	Yes	Yes	Yes
District-Year FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Control Mean	0.02	0.01	0.03
R^2	0.38	0.38	0.36
No. of firms	31,327	31,327	31,327
N	186,726	186,726	186,726

Notes: Merge, Acquire, and Acquired in Columns (1)–(3) are dummy variables that take the value 1 if a firm either merges with, acquires, or is acquired by another firm and zero otherwise. All regressions control for the log of Goods and Service Tax payments. We include firm, district-year, and industry-year fixed effects and weight observations using Synthetic DID weights. Standard errors are clustered at the district level. * is $p < 0.1$, ** is $p < 0.05$, and *** is $p < 0.01$.

access to credit within the banking system and the government during a time when the economy was depleted of 86% of its cash.

8. Alternate explanations and robustness of results

We now provide additional evidence in support of the fact that firms' political connections played an important role in explaining their resilience after the demonetization shock, as opposed to say, connected firms being able to anticipate demonetization, or having more connected directors in general, or these firms being located in districts with a lower severity of demonetization shock, or their downstream position in the production process, etc. We also show that our results are robust to extending the sample to all firm-years for which an outcome variable is reported, as well as using randomization inference to examine the robustness of our inference.

8.1. Did connected firms anticipate demonetization?

It is theoretically possible that politically connected firms had prior knowledge about the government's plans to demonetize the currency. However, all anecdotal evidence as well as articles in the media point to the contrary and strongly suggest demonetization plan was kept very confidential.[26] Nevertheless, in order to rule this possibility out, in Appendix Section H.1, we conduct a placebo analysis in the pre-period (2012–2015), where we move the 'treatment year' back in time. If firms had prior knowledge, we would detect effects in the years leading up to the policy change. To do this, we first define the treatment year to be 2013 so that the *Post* dummy takes a value of 1 for all years after 2013. Similarly in a second regression, we define the treatment year (and corresponding *Post* dummy) in 2014. As reported in Panel A (for 2013) and B (for 2014) of Table H1, we see no differential effects between politically connected and unconnected firms in prior years.

8.2. Political connections or firm characteristics?

A primary concern for our causal identification is that there are unobserved characteristics about firms that make them resilient during a crisis, as well as enable them to acquire political connections. For example, it is possible that dynamic, entrepreneurial directors of firms are able to make social connections to acquire political ties, as well as be able to navigate a crisis better. In financial economics, these would

[26] As reported in a Right To Information (RTI) reply: *"The demonetization decision was taken in the RBI board meeting at 5:30 pm on November 8, 2016, … highly placed sources within the government has revealed how apart from a select few, even senior Cabinet ministers had no clue why a meeting had been called. In fact, to stop any leak of this sensitive information before Prime Minister Narendra Modi announced it to the nation at 8 pm, all cabinet ministers and officials were asked to switch off their mobile phones before entering the meeting."* Source: Outlook India Article, Nov 2021.

be the *high-type* firms. As discussed in Section 5, our empirical strategy mitigates many of these concerns with the help of firm fixed effects as well as the synthetic difference-in-differences strategy. Nevertheless, to further bolster our confidence, we conduct multiple additional analyses.

Connected entrepreneurs and directors. First, we take advantage of our rich data and create alternate measures of firms' connections since we can observe whether a firm has Directors who are on the board of multiple firms, and hence might know other Directors and entrepreneurs through these connections. More formally, as described in Appendix Section G, for each firm i and Director d of this firm, we calculate two measures: (i) the number of other firms that Director d is on the board of; and (ii) the number of other directors that d would know through being on their board. Using these, we then calculate a firm-level measure (averaging across its Directors) on the average number of other firms their Directors are on, the average number of Directors they know, along the number of "above-median" connected Directors that a firm has based on these two measures. We then re-estimate Eq. (2) with these measures of firm connections (political and directorial) and find two insights, as reported in Tables G2 and G3. First, the impact of political connections on firm performance after the crisis is very robust (in both magnitude and direction) to controlling for the impact of firms being more connected more broadly through their board of directors. Moreover, political connections are an order of a magnitude more important than just having a more connected set of Directors. This increases confidence in our results that it is indeed firms' political connections, as opposed to just more connections, which make them more resilient to the crisis.

Cascading effects to indirectly connected firms. We measure whether firms are "indirectly connected" i.e., define a dummy variable that takes a value of 1 if a firm has one or more directors who also serve on the Board of Directors of a connected firm and 0 otherwise. These directors are neither politicians nor bureaucrats themselves but serve on Boards of firms that do. For example, consider a Firm A that is politically connected and Director A is one of its board members. If Director A also serves on the board of Firm B, which is not politically connected, then Firm B is defined as indirectly connected. In total, we identify 13,565 such "indirectly connected" firms. We then redo our analysis to understand how these indirectly connected firms (relative to non-connected ones) respond to the policy shock and report the results in Appendix Section H.2, which clearly shows that firms with indirect political connections do not fare differently than non-connected firms. This is also potential evidence that direct political connections matter for firm performance, as opposed to connections more generally.

Recency of political connections. We turn to a robust finding in the prior literature, which shows that the impact of political connections on influencing firm outcomes weakens with connections that are made farther back in time, as compared to more recent ones (Faccio et al., 2006; Deng et al., 2020). In Appendix Section H.3, we test for this in our sample as well and find evidence consistent with this. In Panel A of Table H3, we utilize the date of the first political connection and define a binary indicator that takes the value 1 for firms having "recently" established political connections i.e., those firms having a political below the median years (4 years), and 0 otherwise. The coefficients for interaction with *recently-established* firms are large and positive whereas those for the interaction with *farther-off* are much smaller. In Panel B, we use the timing of the latest political connection, which is *short-established* if it is less than the median (3 years prior to demonetization), and *long-established* if it is greater than the median. Here again, the short-established political connections matter more (Columns 1 and 3). If firms' entrepreneurial ability or any other firm characteristics instead of political connections were protecting the firms, the firms with father-off or long connections would be just as likely to protect themselves as the firms with more recently formed connections.

Resilience by firm size. We undertake another additional analysis that examines the heterogeneity of our results based on firm size. If larger firms (as measured by those with more income and assets) can (unobservably) deal with crises better and are more likely to acquire political connections, it could threaten our identification strategy. We follow the classification method used by CMIE and classify firms as large if the firm's average total income and assets in the pre-treatment period (from 2012 to 2015) is above the 75th percentile. With this definition, 70% of connected firms are large, as opposed to only 30% of small ones. We then estimate a triple-differences specification to examine whether the impact of political connections on firm responses differs by whether they are large or small. As reported in Table H4, we see that the differential impact of the crisis on politically connected firms as measured in our baseline specification (reported in Panel A) is not driven by larger (as compared to smaller) connected firms (Panel B).

8.3. Correlation between spatial location of politically connected firms and severity of the demonetization shock?

One may be concerned that the politically connected firms are located in districts/areas with less severe shocks. We therefore examine whether the share of politically connected firms in a district (before demonetization) is correlated with the severity of the shock, by calculating the share of politically connected firms in 2015 (the year before demonetization) and regressing it on the standardized value of shock severity of a district.[27] We cluster standard errors at the district level. As reported in Table H5, we find no correlation. Both the estimated magnitude is small, and it is statistically insignificant at conventional levels.

8.4. Correlation between political connections and downstream position of firms

Kisat and Phan (2020) investigate whether the demonetization shock (interpreted as a demand shock) propagated through industry input–output networks. Therefore, it is possible that firms in downstream industries (and hence had a larger shock) are also more politically connected. To examine this, we use the 2015 Input-Output Table to identify the upstream-ness of an industry. We then calculate the fraction of politically connected firms for each of these industries and report it in Figure H2. In this figure, we sort industries by an increasing share of goods in that industry consumed by households, i.e., from "upstream" industries like mining, construction, metals, etc., to more "downstream" ones like hotels, food and beverages, health, real estate, etc. As is evident from the figure, there is no clear pattern in whether upstream or downstream firms are more likely to have political connections, suggesting that (for example) more consumer-facing industries are neither more nor less likely to establish political connections. Either way, we always include industry-year fixed effects in our analysis, which allows us to control for a differential evolution between (say) upstream and downstream industries over time.

[27] We use Figure V from Chodorow-Reich et al. (2020), reproduced as Figure H1, to classify districts into more severely shocked and less severely shocked areas based on whether they had an above or below median demonetization shock index. Chodorow-Reich et al. (2020) define the demonetization shock in a district in the post-demonetization period as the value of legal tenders in the post-demonetization period divided by the total value of cash in that district before demonetization. They construct this shock indicator using currency chest records maintained by the Reserve Bank of India.

8.5. Firms acquiring political connections after the crisis

In our preferred analysis, we use a time-invariant measure of political connections, defined as whether a firm was politically connected before 2016. However, 2.2% of firms in our sample acquired a political connection after 2016 (see Table I1). If anything, this would bias our estimates towards zero and provide a lower-bound estimate of the true impact of political connections. That said, we provide additional tests reported in Appendix Section I. Specifically, in Panel A of Table I2, we re-run our analysis *excluding* firms that established connections post-2016; the results are consistent with our main findings, with slightly larger point estimates. In Panel B, we introduce binary variables for pre- and post-2016 connections, allowing us to control separately for firms that gained connections after the demonetization shock in 2016. Our results remain robust. Notably, even firms that connected post-crisis show improved performance. This implies that political connections matter, but they potentially matter when firms have to respond to a crisis. Appendix Section I provides an elaborate discussion.

8.6. Extending the sample to all firm-year observations

We use a consistent sample of firms across outcome variables in our regressions. However, there is some variation in the availability of outcome variables across firms i.e., some outcome variables are reported for some firms, but not others. We, therefore, redo our analysis (estimating Eq. (2)) using all firms for which an outcome variable is reported. Our results remain qualitatively and quantitatively similar as reported in Appendix Section H.7.

8.7. Randomization inference

As reported in Table H10, we show that our results are robust to clustering standard errors at the firm level. However, we also examine the robustness of our inference using a Randomization Inference (RI) procedure. This test, originally proposed by Fisher (1935) and developed by Heß (2017) and Young (2019), allows for statistical inference by comparing the realized treatment effect with multiple (100) placebo assignments. This procedure, therefore, has the advantage of providing inference with the correct size, regardless of the sample and cluster size. Columns (1) and (2) of Table H11 report the SDID coefficient and its associated p-value from our main analysis respectively. The p-values from the RI procedure (Column 3) are similar to those in Column (2), indicating the robustness of our statistical inference. For some variables such as the log of short-term borrowings, we see a smaller p-value which bolsters our confidence that connected firms have more access to scarce short-term credits.

9. Conclusion

We introduce a new method for identifying firms' political connections through a context-based, machine-learning algorithm that utilizes the social network of politicians and bureaucrats. Using this approach, we build a unique dataset of political connections for Indian firms, revealing that politically connected firms were more resilient following a significant macroeconomic crisis in India. In light of recent global economic disruptions, these findings underscore the importance of firms' political connections. Our analysis also sheds light on the channels through which political connections can play a central role in altering the operational decisions of firms during an economic downturn. In our context, we find that politically connected firms were able to get access to short-term credit, especially from the banking system and the government. Moreover, they were able to delay their payments owed to their suppliers, vendors, and creditors, along with delaying short-term interest and debt payments as well. We think of our analysis as a helpful step in not only providing additional empirical evidence on understanding the role of political connections, but the mechanisms through which they can help firms increase resilience to an economic downturn. Explorations of the interactions with different stakeholders through requests, reputation, threats, etc., are beyond the scope of this study but represent a promising avenue for future research.

CRediT authorship contribution statement

Yutong Chen: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation. **Gaurav Chiplunkar:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sheetal Sekhri:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Anirban Sen:** Resources, Data curation. **Aaditeshwar Seth:** Writing – review & editing, Resources, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2025.103471.

Data availability

The authors do not have permission to share data.

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