Consumer Demand Shocks & Firm Linkages: Evidence from Demonetization in India*

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JEL Codes: O11, E23, G30, E51

*We are grateful to Xavier Giroud, Amit Khandelwal, Ernest Liu, Atif Mian, Ezra Oberfield, and Richard Rogerson for their guidance and support in this project. We would also like to thank individuals at CMIE Prowess, and seminar participants at Princeton University.

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Abstract

Exploiting a unique natural experiment, the 2016 demonetization episode in India, this paper analyzes the extent to which a consumer demand shock propagates through firms' input-output networks. In November 2016, India demonetized 86% of its currency, creating a nationwide demand shock. We construct measures of upstreamness to evaluate the impact of the demonetization shock on firms based on their position in the supply chain. Contrary to the predictions of many network models, we find that the shock does not meaningfully propagate across the supply chain. Revenues, wages, and investment decline substantially after demonetization, but these negative effects are largely limited to consumer facing firms. We identify several mechanisms, such as pricing power, inventory frictions, and export intensity, which independently explain this result. Our findings suggest that final goods producers are particularly susceptible to, and therefore must be protected against, unexpected declines in consumer demand.
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The smooth functioning of a modern economy, across both developed and emerging markets, relies heavily on increasingly complex linkages in its supply chain. Recent empirical evidence shows that firm-level micro shocks propagate to firms' suppliers as well as to their customers (Barrot and Sauvagnat (2016), Carvalho et al. (2020)). Isolated disruptions to a particular sector can in this setting agglomerate to create aggregate fluctuations, an important concern expressed by both economists and policymakers. It stands to reason then that a more large-scale, though sector specific, shock to an economy would also dampen output for initially unaffected industries.

Our paper exploits a unique natural experiment, the 2016 demonetization event in India, to study the role of input-output linkages in propagating a demand shock. In a surprise announcement on November 8, 2016, the Indian government declared that its two largest denomination banknotes, worth 86% of currency in circulation, would no longer be considered legal tender as of midnight. The episode created a nationwide liquidity shock; cash withdrawals and exchanges were restricted as the government was slow to print new replacement notes. The event occurred in an otherwise stable macroeconomic environment and did not create a concurrent shock to wealth or to other key monetary policy variables such as the interest rate and central bank liabilities.

Consumer facing industries in India were most exposed to the initial shock created by demonetization, though frictionless network models predict that the shock should eventually spread to non-consumer facing industries as well. Contrary to money neutrality predictions in benchmark New Keynesian models, a shock to consumer cash holdings in India had a meaningful negative economic impact (Chodorow-Reich et al. (2019)). Moreover, final goods producing industries were particularly vulnerable to demonetization as cash transactions in India are heavily concentrated in the consumer sector, with both durable and non-durable goods often purchased in cash. Theoretical network models with perfect competition and constant returns to scale production functions, as well as recent empirical results in the literature, predict however that any demonetization induced shock should pass-through to intermediate goods producers.

In contrast to these predictions, our paper finds that the demonetization shock disproportionately affects consumer facing industries, and does not meaningfully propagate upstream. We document several channels, such as pricing power, exports, and inventory stickiness that may explain this result. To the best of our knowledge, our paper is also the first to investigate the propagation of a demand shock through a supply chain in a developing economy.

In order to trace out the effects of demonetization across firms at different nodes along the supply chain, we adopt an "upstreamness" measure (Antràs et al. (2012a)) that is commonly used in the firms networks literature. An industry's upstreamness can be interpreted as a (weighted) average distance from final use for the goods it produces.[1] To construct this measure, we need an input-output table which describes the sale and purchase relationships between goods producers and goods users within an economy. We use the 2015-16 Indian Annual Survey of Industries (ASI) to construct an input-output table for India at a five digit industry level. The ASI is an annual, nationally representative survey of manufacturing establishments in India. While using the ASI, we can generate detailed upstreamness measures for manufacturing firms, we do not capture non-manufacturing firms that tend to be more consumer facing. To address this deficiency, we also construct a coarser measure of upstreamness based on the official supply use tables published annually by the Indian Ministry of Statistics and Programme Implementation (MOSPI).

Our empirical strategy is a difference-in-difference design which compares outcomes in the periods after demonetization for industries with high upstreamness (that are more likely to contain firms producing intermediate goods) to industries with low upstreamness (that are more likely to contain firms producing final goods). We examine the impact of demonetization on firm performance outcomes—total revenue and wage expense—as well as firms' decisions related to capital expenditure investments. Firm data is sourced from databases managed by the Centre for Monitoring Indian Economy (CMIE). Our preferred empirical

[1] Another interpretation for upstreamness is the dollar amount by which output of all sectors increases following a one dollar increase in value added in sector j.

specification includes $State \times Period$ fixed effects to flexibly control for spatial heterogeneity in the impact of demonetization, as shown in Chodorow-Reich et al. (2019).

We first document that firms with higher upstreamness values (upstream firms) perform consistently better than firms with lower upstreamness values (downstream firms) in the periods after demonetization. A unit increase in upstreamness is associated with 3.3% to 8.3% higher quarterly revenues post-shock. This difference in revenue primarily comes from revenue *reductions* experienced by downstream firms. This result is in line with raw revenue trends in the periods around demonetization, and is consistent across both the ASI and MOSPI measures of upstreamness. We also evaluate wage outcomes and find that post-demonetization, upstream firms' wages are 3.2% to 4.2% higher relative to downstream firms. Both our revenue and wage results are robust to non-parametric definitions of upstreamness and of time periods. Taken together, these results suggest that the negative impact of demonetization did not substantially "pass-through" across the supply chain.

Independent of pass-through considerations, both demand and supply side mechanisms can theoretically generate the above results. First, upstream firms could experience higher productivity than downstream firms in the periods after demonetization, raising both their revenues and wages. However, this hypothesis is only valid if there was a positive productivity shock that disproportionately affected upstream firms in the exact same quarter as demonetization. To the extent that demonetization itself may have created a supply side shock, through a reduction in credit supply for instance, it is unclear why such a shock would particularly impact downstream firms' performance, as our results seems to suggest. A second, more plausible, explanation is that demonetization produced a liquidity shock that primarily affected retail customers and therefore, at first order, negatively impacted downstream firms' performance.

While the effects of demonetization on firm performance documented thus far can be viewed as short-term, demonetization can also impact decisions that may affect firms' longer term prospects. Capital investment projects are critical to the long-term performance of a firm and require the commitment of a significant amount of a firm's economic resources. These projects, which range from purchasing additional equipment to building a new factory, allow companies to maintain or increase the scope of their operations. A large literature in economics and finance has documented that managers reduce capital expenditures during periods of macroeconomic uncertainty (Baker et al. (2016), Gulen and Ion (2016), McLean and Zhao (2014)). We find that a unit increase in upstreamness leads to a higher capital expenditure relative to fixed assets at economically significant levels. Using granular project level data, we investigate the impact of demonetization on the managerial decisions to start or complete capital expenditure projects and find that both margins are affected. We document that a unit increase in upstreamness leads to a 3 to 9 percentage points (p.p.) increase in the likelihood that an ongoing capital project will be completed in a given quarter. On the other side of the project life-cycle, we find that after demonetization, upstream firms initiate 1% to 2% more new capital projects relative to downstream firms.

We evaluate several independent mechanisms that may drive the lack of pass-through of the demonetization shock to upstream firms, and find evidence for all our considered explanations. First, we propose a "pricing channel", whereby the shock reduces demand primarily through a reduction in prices rather than quantities of final goods consumed. Consistent with the predictions of this channel, we find that profit margins are significantly lower for downstream firms post-shock. Second, we explore whether frictions in inventory contracts disincentivize downstream firms from adjusting their material goods purchases. We find that inventory turnover, a proxy for how efficiently a firm converts its inventory to sales, declines for downstream firms post-shock. Lastly, we examine the role of exports. In India, an industry's export intensity increases with upstreamness. Upstream firms may therefore be able to boost exports more readily in response to a demand decline. We explore heterogeneity in our results by a firm's export intensity, and find that conditional on upstreamness, firms classified as exporters have higher revenues post-shock.

We consider a battery of research design choices to confirm the robustness of our results.

Our baseline results remain robust to variations on sample selection, regression specifications, and variable measurement.

Our project contributes to three strands of literature in macroeconomics and finance. First, we are linked to the empirical literature on the role of input-output linkages in transforming microeconomic shocks into aggregate fluctuations (Carvalho and Tahbaz-Salehi (2019), Boehm et al. (2019)). Carvalho et al. (2020) analyze supply chain disruptions created by the Great East Japan Earthquake of 2011, and find that both the suppliers and customers of firms located near the disaster area experience a decline in performance. Similarly, Barrot and Sauvagnat (2016) study natural disasters in the US and find that firms report 2 to 3 percentage points lower revenue growth when their suppliers are affected by a major disaster.

Our paper contributes to this literature by considering features of the supply chain that may prevent rather than facilitate the transmission of sector specific shocks. The literature on input-output networks has so far centered on features of a production network, such as input specificity, that result in a productivity shock propagating from a *supplier* to its *customer*. By exploiting a shock that initially impacts final goods producers, we instead identify features specific to this sector, such as stickiness in inventory orders and pricing power, that end up dampening rather than facilitating shock propagation.

Our research is also linked to the extensive literature on production network frictions (Baqaee (2018), Liu (2019)). Papers in this literature identify frictions in the production process, usually modelled as "wedges", which either agglomerate to create aggregate distortions (Bigio and La'O (2020)), or amplify the effect of an idiosyncratic firm shock (Altinoglu (2020)). Our work builds on this research by providing reduced form evidence for an environment where similar wedges may actually dampen the propagation of a shock, provided that the initial shock is felt by consumers. Consider the results in Boehm and Oberfield (2020), who find that enforcement frictions created by congested courts in India incentivize plants to shift away from consuming non-homogeneous intermediate inputs. If a negative demand shock hits these plants, existing enforcement frictions may then in fact dampen shock propagation, as the plants are less reliant on intermediate goods to begin with.

Finally, our work also speaks to both the theoretical and empirical research on money non-neutrality, particularly in emerging market economies (Lucas and Stokey (1987), Velde (2009), Karmakar and Narayanan (2020)). We are most closely linked to Chodorow-Reich et al. (2019), who also study the Indian demonetization episode and find that economic activity declines substantially in relatively more cash constrained districts. Our paper augments this literature by considering the heterogeneous effects of a money supply shock by industry. In particular, we are able to show that even if a shock to money holdings is large scale and widespread, intermediate goods sectors may be able to emerge from it relatively unscathed.

The rest of the paper is structured as follows. Section 1 provides background on the 2016 Indian demonetization episode. Section 2 reviews the data sources used for the project. Section 4 presents our baseline results, and Section 5 explores additional mechanisms behind the results. Section 6 overviews our various robustness checks and Section 7 concludes.

1 Demonetization

In an unscheduled televised address at 8:15pm on November 8, 2016, Prime Minister Narendra Modi announced that the two largest denomination banknotes in India, the INR 500 and INR 1,000 notes,[2] would no longer be considered legal tender as of midnight, and would be replaced by new INR 500 and INR 2,000 notes (Modi (2016)). At the time of the announcement, the banned notes accounted for 86% of outstanding currency in circulation. The justification for the policy was to counter black money, terrorism financing, and corruption. Individuals were given fifty days, until December 31, 2016, to deposit the old notes at banks or post office accounts.

The demonetization event created a nationwide liquidity shock. To maintain secrecy, the Indian government had not printed enough replacement notes on the eve of the announcement. Consequently, cash availability was significantly reduced. Over the counter

[2]worth around \$8 and \$15, respectively at historical exchange rates.

cash exchanges were limited to INR 4,000 per day (up to a limit of INR 10,000 per week), and cash withdrawals from bank accounts were restricted to INR 10,000 per day (up to a limit of INR 20,000 per week). ATM withdrawals were also limited to INR 2,000 per day. Importantly, there were no restrictions placed on non-cash modes of payment, such as credit card, debit cards, and cheques.

The insufficient availability of new notes led to a persistent decline in currency in circulation; however, the Reserve Bank of India's (RBI's) overall liability position and monetary policy rates remained mostly unaffected. Figure 1 plots the indexed path of total currency in circulation as well as RBI outstanding liabilities. As shown in the figure, currency balances fell by 50 percent in the immediate aftermath of demonetization, and remained below their pre-demonetization values even until the end of 2017. Conversely, RBI total liabilities remained steady during this period, as deposits and RBI issued market stabilization bonds (MSBs) increased to offset the currency decline.[3] The RBI's official policy rates, as well as private borrowing and lending rates changed little in the aftermath of demonetization. Furthermore, according to the RBI's own estimates, 99% of the banned notes were eventually returned back to the central bank by mid-2018 (RBI (2018)). Taken together, these facts suggest that demonetization created biting cash shortages but did not lead to a concurrent wealth or monetary policy shock.

While demonetization driven cash constraints were imposed on firms throughout the supply chain, indicative evidence suggests that consumer facing industries may have been the most adversely affected. India's currency to GDP ratio, at 11%–12%, is one of the highest among peer economies (BIS (2018)). Indian consumers primarily use cash to purchase a variety of both non-durable and durable goods.[4] In the wake of demonetization, consumer facing industries as varied as luxury cosmetics and automobiles were negatively impacted. The CEO of Sephora, for instance, predicted a 20—25% loss in sales until December 2016.

[3] MSBs were interest paying government bonds issued by the RBI to absorb the surge in bank deposits created by demonetization.

[4] See https://www.ft.com/content/e52dab06-b093-11e6-a37c-f4a01f1b0fa1 for a summary of the sectors most likely to be affected by demonetization.

Sales of passenger two and three-wheelers recorded their largest decline in 18 years.[5] These results indicate that consumers did not sufficiently substitute away from cash towards non-cash forms of payment after the shock. Demonetization also does not seem to have led to a more long-term reduction in Indian consumers' cash reliance. Indian households' cash holdings rose to 2.8% of GDP as of fiscal year end 2018, the highest level in almost a decade (RBI (2018)).

2 Data

2.1 Annual Survey of Industries

We use the 2015-16 Indian Annual Survey of Industries (ASI) to construct an input-output table for India at a five digit industry level. The ASI is an annual, nationally representative survey of formal sector manufacturing establishments in India.[6] It covers all establishments with greater than 100 employees, and one-fifth of all establishments with greater than 20 employees.[7] The survey's reporting year runs from April 1st through March 31st of the following year. We source data from the 2015-16 round as it was the most recent pre-demonetization survey available.

The 2015-16 ASI includes input and output schedules that detail, at a product level, each establishment's intermediate input use and outputs. Product codes are reported according to the National Product Classification for Manufacturing Sector (NPCMS), a 7-digit standardized classification that covers all manufacturing sector products in India and contains around 5,000 unique product codes.[8] Each establishment is also assigned a 5-digit indus-

[5] https://www.livemint.com/Industry/n8yj3dvEdJqlhPytT8buNN/Auto-sales-plunge-most-in-16-years-on-Narendra-Modis-demone.html.

[6] Many papers in the literature have used the ASI to analyze the Indian manufacturing sector. Prominent examples of these include Hsieh and Klenow (2009, 2014), and Boehm and Oberfield (2020)

[7] These thresholds vary slightly by state. For instance, the ASI covers all industrial units in the seven less developed states and union territories (e.g., Arunachal Pradesh). For more information, see the "ASI Instruction Manual 2015-16", available at http://microdata.gov.in/nada43/index.php/catalog/143.

[8] The first 5 digits of the product code is based on the United Nation's Central Product Classification (CPC). The 2015-16 ASI reports product codes according to the 2011 version of the NPCMS.

try code according to the National Industrial Classification (NIC), India's standard coding scheme covering all industries.[9]

We construct an input-output matrix at a 5-digit industry level using the input and output schedules. Our procedure is as follows: First, from the output schedule, we determine the primary industry that produces a particular NPCMS product. This mapping is appropriate, as a product is mostly produced by one primary industry (see Figure A.1). Second, we assign each product in the input schedule to its respective primary producing industry. Finally, we consolidate the input data at an industry level, and impute an industry's final goods production based on the difference between its total output and its intermediate uses as reported in the consolidated input schedules. The procedure is highly successful; we are able to create an input-output matrix for 514 out of 658 total industries in the ASI, which account for 96% of total output in 2015-16.

2.2 MOSPI Supply Use Tables

We also construct an input-output matrix at a coarser level based on the official supply use tables published annual by the Indian Ministry of Statistics and Programme Implementation (MOSPI).[10] MOSPI reports input-output data for 66 industrial sectors in India. While this data is not as detailed as the ASI, it has broader coverage, including all agriculture and service sectors. The reported value added and expenditure figures also align with country-wide GDP estimates. Consistent with the ASI data, we use the 2015-16 supply use tables for our analysis.

The input-output matrix for the MOSPI data is constructed following a similar procedure to that used for the ASI. From the supply table, we determine the primary producing industrial sector for a particular commodity listed in the use table. The exercise yields input-output data for all 66 industrial sectors in India.

[9]The 2015-16 ASI reports NIC-2008 industry codes, which are based on ISIC-rev. 4.

[10]Available at http://mospi.nic.in/publication/supply-use-tables.

2.3 Firm & Investment Data

We utilize two databases maintained by the Centre for Monitoring Indian Economy (CMIE). The first database, Prowess, provides information from firms' financial statements. Prowess covers both listed and unlisted firms with sales greater than INR 40 million (approximately 625,000 USD). Unlisted firms account for approximately 25% of the raw dataset. Prowess provides financial statement data at both the consolidated parent and standalone subsidiary level. We conduct our main analysis at the subsidiary level to better isolate the impact of demonetization on firm performance since consolidated firms can have multiple subsidiaries located at different points along the supply chain. From Prowess, we extract subsidiary level quarterly revenue, profitability, assets, and liabilities for the periods ranging from 2015Q1 to 2017Q4.

We follow Chodorow-Reich et al. (2019) and seasonally adjust firm performance variables as reported in Prowess. The raw data for P&L items such as revenues displays significant quarterly seasonality. To strip out seasonal factors, we adopt the following procedure: for each firm that reports outcomes from 2014-2015, we regress a firm variable (e.g., revenues) on quarter dummies and a linear time trend. The seasonally adjusted variable is computed as the unadjusted variable residualized on the quarter dummies. Our main results are robust to including non-seasonally adjusted data (section 6).

The second database, CapEx, records detailed information on investment projects with a minimum cost of INR 10 million that involve the setting up of new capacities. Examples of such projects include the building of a new production facility or the purchase of additional machinery. CMIE relies on several data sources for information about these projects including publicly available reports from the companies implementing the project. For each project, we obtain from CapEx the start date, completion date (if completed), industry, implementing company, and the Indian state in which the project is located.

2.4 Upstreamness Calculation

Following Antràs et al. (2012a), we compute upstreamness at the industry level for India.[11] Upstreamness is a standard statistic that is widely used in the firm networks literature. It is computed by assigning discrete weights based on the distance from final use of an industry's output. To build intuition, we show how to compute upstreamness for a closed economy with N industries.[12] Each industry j's output, Y_j can be written as follows:

$$Y_j = F_j + Z_j = F_j + \sum_{k=1}^{N} d_{kj} Y_k \tag{1}$$

where F_j and Z_j are the sum of industry j's output used as a final good and an intermediate good, respectively. Z_j can be disaggregated as $\sum_{k=1}^{N} d_{kj} Y_k$, where d_{kj} is the rupee amount of industry j's output used to produce one rupee worth of industry k's output, Y_k. Iterating forward on this expression, we obtain an expression for industry j's output as an infinite sum of its use along all positions in the value chain:

$$Y_j = F_j + \sum_{k=1}^{N} d_{kj} F_k + \sum_{k=1}^{N} \sum_{l=1}^{N} d_{jl} d_{lk} F_k + \dots \tag{2}$$

Industry j's upstreamness U_j is defined as the weighted average of each of the RHS terms in (2) normalized by Y_j, where the weights equal one plus each term's distance from final use:[13]

$$U_j = 1 \cdot \frac{F_j}{Y_j} + 2 \cdot \frac{\sum_{k=1}^{N} d_{kj} F_k}{Y_j} + 3 \cdot \frac{\sum_{k=1}^{N} \sum_{l=1}^{N} d_{jl} d_{lk} F_k}{Y_j} + \dots \tag{3}$$

From the above expression, it is clear that U_j increases with "distance" from the final con-

[11] We thank the authors for making their code available for public use.

[12] Extending these results for an open economy requires a simple adjustment to the weights. See Antràs et al. (2012a,b) for more details.

[13] In matrix notation, industry j's upstreamness equals the j-th element of the $N \times 1$ matrix $[I - D]^{-2} F$, where D is an $N \times N$ matrix with d_{ij} as its (i, j)-th element, and F is a final goods vector with F_j as its j-th entry.

sumer, and that it is always greater than or equal to one. A value of one implies that an industry is completely consumer facing i.e., it has no intermediate uses. A difference in upstreamness of one unit, a key basis for our reduced form results in section 4, can therefore by interpreted as comparing an industry that sells all of its output to a final consumer to an industry that sells the equivalent of all of its output to another, entirely final goods producing, industry.

We calculate upstreamness for our constructed input-output tables from the ASI and MOSPI, hereafter referred to as ASI upstreamness and MOSPI upstreamness, respectively. For any 5-digit industries in the sample for which we cannot compute ASI upstreamness, we determine upstreamness for the associated 4-digit industries and assign the variable at this higher consolidation level.[14] In addition, to increase coverage to non-manufacturing industries, we manually input an ASI upstreamness value of one for those industries that report a MOSPI upstreamness of one or very close to one.[15] We show in Section 6 that our results are robust to these adjustments. In order to assign MOSPI upstreamness to a firm, we map each MOSPI industrial sector to its associated NIC industry at a 3 digit industry level based on the industry names reported in the MOSPI SUT documentation.

The distribution of ASI and MOSPI upstreamness for our sample firms, plotted in Figure 2, shows significant variation in upstreamness, with a large proportion of firms reporting an upstreamness of close to one. Relative to ASI upstreamness, MOSPI upstreamness has a less smooth distribution, which is to be expected as it is based on a coarser input-output matrix. Additionally, a greater proportion of firms report higher values of MOSPI upstreamness. This result is intuitive, since our MOSPI input-output table includes all agriculture and service sector industries, and so contains longer input-output linkages on average.

[14] We repeat the procedure up to a 3-digit level.

[15] The exact threshold used is a MOSPI upstreamness of less than or equal to 1.10.

2.5 Sample Selection and Statistics

To examine the effect of upstreamness on firm performance, we merge the measures generated from either the ASI or MOSPI to firms in CMIE's Prowess database by industry. For cases where the firm's industry is only available at less granular levels, we impute its upstreamness with the average upstreamness for all industries within the less granular industry sector.[16] We restrict our analysis to a balanced panel of firms for the twelve quarters between 2015Q1 and 2017Q4.

A hurdle to analyzing investment data is that the system CMIE used to classify a projects' industry is not consistent with the India's official National Industrial Classification (NIC), the industry classification that our upstreamness measures are based on. However, the CMIE does provide a linktable between the NIC industries to its own proprietary industry classification. Because the CMIE's industry classification contains fewer industries, the linktable is a many to one match. Thus, we collapse the upstreamness measure by taking an average across unique NIC industries within a CMIE industry. We focus on firms with projects outstanding—projects that have been announced and are under implementation—between 2015Q1 and 2017Q4.[17]

The sample we employ to assess the effect of demonetization on firm performance consists of more than 2,500 unique private and public companies. Table 1 presents the summary statistics.[18] On average the firms in our sample make about INR 1,780 million in revenue per quarter. The revenue distribution is skewed on the right tailed as the median quarterly revenue is only INR 416 million. Similarly, average wages paid is INR 145 million per quarter,

[16] To be clear, ASI upstreamness is computed at the 5-digit industry level. For all firms for which industry is only available at the 4-digit industry level, we impute its upstreamness as the average upstreamness of all 5-digit industries within the 4-digit industry sector. We follow a similar process to merge MOSPI upstreamness with Prowess. For all firms for which industry is only available at the 2-digit industry level, we impute its upstreamness as the average upstreamness of all 3-digit industries within that 2-digit industry sector.

[17] This criteria eliminates firms that start and complete capital expenditure projects before 2015Q1 and did not start any projects between 2015Q1 and 2017Q4. Our reason for implementing this filter is because of the lumpy nature of capital expenditures and firms that did not have an outstanding project in the years before and after demonetization are less likely to consider capacity expansion as a relevant decision option during this time.

[18] For variable definitions, see Appendix B.

while the median wage expense is INR 36 million. Turning to control variables, the mean firm age is 34 years with INR 1,828 million in assets. On average firms spend 6% of net fixed assets on capital expenditures every semester. The average firm leverage—defined as total debt over total assets—is 27% and the average annualized return-on-assets—defined as net income over total assets—is 2.52%.

To illustrate the impact of demonetization on firm performance, we divide the firms in our sample into terciles according to both the ASI and MOSPI upstreamness measures. We then run a regression of log revenues on firm fixed effects and period indicators, with 2016Q3 as the leave out period. For each tercile of upstreamness, Figure 3 plots the point estimates and the associated confidence intervals for each period relative to 2016Q3. Panel (a) and panel (b) plot estimates for ASI upstreamness and MOSPI upstreamness, respectively. The two panels show that both downstream (tercile 1) and upstream firms followed similar revenue trajectories prior to demonetization. However, after the shock, downstream firms suffered a significant revenue decline, while upstream firms' revenues remained largely on their existing paths.

3 Empirical Strategy

Our main empirical strategy is a difference-in-difference design, where industry level variation comes from our upstreamness measure. The baseline estimating equation is as follows:

$$y_{fjt} = \beta(U_j \times \mathbb{1}\{Post_t\}) + \delta^T \mathbf{X}_{fjt} + \mu_f + \gamma_t + \varepsilon_{fjt} \tag{4}$$

where f indexes firm, j indexes industry, and t indexes time period (at a quarterly frequency). y_{fjt} is the firm-level outcome variable of interest which includes revenues, wage expense, and investment variables. U_j is our constructed measure of industry upstreamness, computed as outlined in Section 3 above. We also consider a more non-parametric specification where we replace U_j with a binary variable that equals one if a firm belongs to an industry in the bottom tercile of the upstreamness distribution (as presented in Figure 2). We refer to these firms as downstream firms. $\mathbb{1}\{Post_t\}$ is an indicator variable that equals one for all calendar quarters after demonetization occurred (i.e., 2016Q4 onward). $\mathbf{X}_{fjt}$ is a vector of firm level controls, which includes firm size, leverage, return-on-assets, and age.

In our main specification, we fix control variables in the period before demonetization (i.e. 2016Q3) and interact them with the period indicators, thus allowing observed differences in firm characteristics to non-parametrically affect outcomes. We favor this approach as it mitigates (1) simultaneity bias stemming from certain controls (e.g. return-on-assets) being jointly determined with our outcomes and (2) the "bad control" problem since some firm level attributes are themselves affected by demonetization (Angrist and Pischke (2008)).[19] μ_f and γ_t are firm and period fixed effects, respectively, and ε_{fjt} is the error term. The coefficient of interest is β, which measures the differential impact of a unit increase in upstreamness on various firm level outcomes after demonetization occurred.

In our most stringent specifications, we modify firm and period fixed effects into $Firm \times Quarter$ fixed effects and $State \times Period$ fixed effects, respectively. Including $Firm \times Quarter$ fixed effects allows us to flexibly control for quarterly seasonality in the outcome variables.[20] By adding $State \times Period$ fixed effects, we control for differential reactions to demonetization (for instance, the order in which certain states received newly printed notes) at a state level. Our design therefore isolates the relative impact of demonetization for consumer facing industries *within* a particular state.

3.1 Identification

The identifying assumptions underlying our estimation strategy are as follows: First, both upstream and downstream firms exhibit similar revenue and wage *growth* in the periods prior to demonetization. Second, in the absence of demonetization, revenue and wage growth

[19] In Section 6, we show that our results are robust to using time varying firm characteristics (lagged by a year) as controls.

[20] To the extent that seasonality is not captured by our seasonal adjustment algorithm.

would have continued to follow similar trends across upstream and downstream firms. We test the former assumption by running the following non-parametric version of our main specification:

$$y_{fjt} = \sum_{t \neq Q3'16} \beta_t (U_j \times \mathbb{1}\{Period = t\}) + \delta^T \mathbf{X}_{fjt} + \mu_f + \gamma_t + \varepsilon_{fjt} \tag{5}$$

where the common variables and indices are exactly as in (4). $\mathbb{1}\{Period = t\}$ indicates a particular quarterly period. The left out period is the quarter prior to demonetization, 2016 Q3. In the absence of pre-trends, we would expect the β_t coefficients associated with the pre-demonetization periods to be close to zero.

Including $State \times Period$ fixed effects allows us to partly address the second identifying assumption. This approach allows us to flexibly control for any concurrent changes in state policies during the sample period. Furthermore, to the extent that demonetization created a supply shock, it is unlikely to affect firms that report in the Prowess database. Informal sector firms in India may have experienced a productivity shock from demonetization, as they pay their workers mostly in cash. However, given the large revenue base and formal nature of firms in our sample, it is improbable that these firms' ability to pay their workers was curtailed by restrictions on cash availability.[21]

4 Main Results

4.1 Firm Performance

In our initial analysis, we focus on two measures of firm performance: total revenue and total wage expense. Our choices are motivated by the impact of demonetization on consumers. First, if by eliminating large bills, demonetization affects consumers' ability to transact using

[21] Note that even if firms in our sample pay workers in cash, our assumption that demonetization primarily created a demand shock would only be violated if final sector firms pay a disproportionate factor of their workers in cash relative to intermediate goods producers. We address this concern by flexibly controlling for firm observables (such as firm size) that may correlate with payment practices.

cash, this could translate to lower revenue for firms that are more consumer facing. These firms are precisely the downstream firms—firms with low upstreamness—in our sample. While the impact of this demand shock can be passed on by downstream firms to more upstream firms leading to lower revenue for all firms throughout the supply chain, Figure 3 suggests that this is not the case. Second, these downstream firms could respond to reduced revenue by cutting workers or by growing employed labor at a slower rate, leading to lower wage expense relative to upstream firms.

4.1.1 Non-Parametric Difference-in-Difference

We formalize the graphical trends displayed in Figure 3 by modifying (4) and replacing U_j with a binary variable indicating a downstream industry, and including a separate indicator for $\mathbb{1}\{Post_t\}$.[22] This approach allows us to confirm that our treatment effect is based off of a *decline* in post-shock performance for downstream firms.

Table 2 presents the results from this analysis, and shows that downstream firms' revenues declined substantially post-shock, whereas revenues for upstream firms were largely unaffected. Columns (1) and (2) report results with firm fixed effects and $Firm \times Quarter$ fixed effects, respectively. The specification in column (3) adds $State \times Period$ fixed effects to replicate our full parametric specification. The specification in columns (4)-(6) replicates columns (1)-(3), and includes controls. Our independent variable of interest is the interaction term $(UpstreamnessTerc. = 1) \times Post$. As shown in the table, the coefficient on this interaction term is negative and statistically significant, indicating that downstream firms have lower revenue relative to upstream firms in the periods after demonetization. The magnitude of the effect ranges from 5.5% to 7.6% depending on the specification. The results for wages are also consistent with those for revenues, as shown in Table A.1. Notably, the *Post* variable is not statistically significant across any of our specifications. This result supports the trends shown in Figure 3, and confirms that downstream firms experienced a revenue

[22] We are therefore unable to include period fixed effects, and so instead include a linear time trend for this specification.

decline after demonetization was implemented, whereas upstream firms' performance was largely unaffected.

4.1.2 Continuous Difference-in-Difference

Table 3 reports the results from estimating (4) for log revenues, where the treatment variable is our preferred continuous measure of upstreamness, and shows that revenues for downstream firms are consistently lower post-shock. Because a higher upstreamness value implies that a firm is less likely to be a final goods seller, the predicted sign of the coefficient on the $Upstreamness \times Post$ interaction term is positive. Panel A and panel B report estimates for the ASI upstreamness and MOSPI upstreamness measures, respectively. Across all specifications, the coefficient on the interaction term is positive and statistically significant. As shown in column (1) of Panel A, a one unit increase in the upstreamness measure leads to higher revenue of about 7.4%. The coefficient remains relatively stable as we add more stringent fixed effects, such as $Firm \times Quarter$ and $State \times Period$ fixed effects in columns (2) and (3), respectively. Adding controls to the specifications in columns (1)-(3), as shown in columns (4)-(6), respectively, we find that a unit increase in upstreamness leads to approximately 8% higher revenues. In Panel B, the coefficient on the interaction term remains positive and statistically significant across a battery of fixed effects structures and controls, albeit with a smaller magnitude.

Table 4 reports the results for total wage expense, and shows that a one unit increase in upstreamness leads to higher wage expense after demonetization of around 3.2-4.2%, depending on the specification. The results are not statistically significant (or marginally significant) for ASI upstreamness but are strongly significant for MOSPI upstreamness. The smaller magnitude in comparison to the results for revenue is suggestive of adjustment costs—firms may not find it optimal to cut labor or reduce hiring in response to an ex-ante temporary shock.

We allow for the effect of demonetization to vary non-parametrically by period, and find revenue and wage results consistent with our parametric specification. Figure 4 plots the point estimates and the associated confidence intervals for both revenue and wages from estimating (5). Panels (a) and (b) show results for ASI upstreamness, and panels (c) and (d) display results for MOSPI upstreamness. Two features of each graph stand out. First, in line with the parallel trends assumption, the estimated treatment effects are largely close to zero and statistically insignificant for each quarter before up to the quarter before demonetization. Second, the estimated treatment effect jumps discontinuously in 2016Q4, the quarter of demonetization. This discontinuity further reinforces the argument that responses are due to demonetization as a shock which restricts consumers' liquidity is more likely to impact firms' revenue and wages immediately whereas confounding variables may have limited reasons to jump discontinuously around the demonetization quarter.

4.2 Firm Investments

Demonetization's direct impact on revenue can spillover into firms' capital expenditure decisions. Capital projects allow firms to increase production or servicing capability and determine firms' long run profitability and growth. A large economic and finance literature documents a strong negative relationship between firm-level capital expenditures and the aggregate level of uncertainty (Baker et al. (2016), Gulen and Ion (2016)). The months subsequent to demonetization epitomize these periods of high economic uncertainty, given that the policy was released in a sudden announcement made by Prime Minister Modi in 2016Q4. Theories of real options predict that the value of managements' option to delay investment increases in macroeconomic uncertainty, incentivizing a halt in investment. Furthermore, demonetization's direct effect on revenue via reduced consumer demand can influence managerial investment decisions if some portion of capital projects are funded with internal funds (McLean and Zhao (2014)). We test these predictions in this section.

We first investigate the effect of demonetization on firm investments by using the capital expenditures line item. The field is typically recorded on the cash flow statement but the

Indian accounting standards only require filing this statement on an annual basis. Additionally, certain balance sheet items are only available on a half year basis. Thus, we back out capital expenditures using the following formula: $FA_t - FA_{t-1} + Dep_t$, where t and $t-1$ represent current and previous fiscal semesters, respectively. FA indicates net fixed assets (e.g. property, plant, and equipment) and Dep indicates depreciation expense.[23] To account for the fact that the amount spent on capital is higher if the *stock* of capital is larger, we scale the imputed capital expenditure value by fixed assets.

We estimate (4) for our capital expenditure outcome variable, and show in Table 5 that a unit increase in ASI upstreamness leads to a higher capital expenditure ratio relative to the mean of about 13% to 20%, depending on the specification.[24] Using MOSPI upstreamness results in a smaller but still statistically significant magnitude that is 10% to 13% of the mean ratio.

The CMIE also provides detailed data on individual capital investment projects. We examine the likelihood of an active project being completed in a given quarter as demonetization could delay projects if firms face difficulties in funding their implementation. As stated in section 2.5, we limit the sample to firms with outstanding projects between 2015Q1 and 2017Q4, and run the following linear probability model:[25]

$$\mathbb{1}\{Complete_{pjt}\} = \beta(U_j \times \mathbb{1}\{Post_t\}) + \eta_p + \gamma_t + \varepsilon_{psq} \tag{6}$$

where the common variables and indices are exactly as in (4). A project p in industry j is an observation in our dataset beginning in the quarter of the project start date until the quarter of the project completion date. That is, the project exits the dataset the quarter after it was completed. The variable $\mathbb{1}\{Complete_{pjt}\}$ turns on the quarter the project is completed. Thus, our specification can be thought of as a linear probability model analog to a hazard

[23]Note that our measure of capital expenditure is net of any asset disposals that occur within the semester and consequently can take on negative values.

[24]$0.008/0.06 \approx 13\%$, $0.012/0.06 \approx 20\%$

[25]In untabulated tests we maintain the same time periods (2015Q1-2017Q4) but expand the sample to projects that are completed by 2019Q4 and find similar results.

analysis. Because we observe limited information on project level characteristics (e.g. costs, labor intensity, etc...), we include project fixed effects, η_p, to rule out the impact of these time invariant omitted variables on project completion.

In Table 6, we examine the extent to which upstreamness and therefore the intensity of exposure to demonetization affects project completion. In Column (1) of Panel A, we find that a unit increase in ASI upstreamness leads to a higher probability of a project being completed in a given quarter. Moving across columns, we find that the effect remains relatively stable as we add more stringent fixed effects, including those that control for the state where the project is located and for seasonality in completion rate. We are careful in interpreting the effect as coefficients in a linear model does not necessarily translate to a marginal effect in terms of probability. Nevertheless, given that the average quarterly completion rate is 0.18 for our sample, we interpret the magnitudes of 0.075 to 0.089 to represent substantial increases in likelihood of completion in a given quarter. In Panel B, we find similar results for MOSPI upstreamness, though the coefficients are smaller in magnitude—approximately 0.03 across all specifications.

In addition to delaying completion of projects, firms also choose not to initiate new projects due to demonetization. We sum all project starts in a given quarter to the firm level for the set of firms identified above—firms with projects outstanding between 2015Q1 and 2017Q4. If a firm has multiple projects during this period, we average upstreamness across all projects tied to a given firm. All firm-quarters during this time period in which the firm did not start a new project are coded as zero. The fixed effect structure are the same as in Equation 4. We find in Table A.2 that the effect of upstreamness is weaker for project starts. A unit increase in upstreamness leads to 1.6-1.7% more project starts in a given quarter though the effect is not strongly significant.

5 Mechanisms

This section considers several potential mechanisms underlying our baseline result of a relative lack of pass-through of the demonetization induced demand shock to upstream industries. Section 5.1 considers the relevance of price responses, section 5.2 tests for inventory stickiness, and 5.3 tackles the importance of exports.

5.1 Profit Margins and Pass-Through

We test whether demonetization induced a disproportionate decline in profitability for downstream firms. The demand shock may have reduced both the prices and the quantity of final goods and services. However, if the shock acts primarily through price rather than quantity reductions, then it is possible that downstream firms' intermediate goods purchases are less affected as these firms are still selling a similar *quantity* of goods. Under this hypothesis, hereafter referred to as the pricing channel, the corresponding intermediate goods suppliers would not see a large reduction in their own revenues, thereby mitigating shock pass-through.

We use profit margins as the key outcome variable to obtain reduced form evidence for the pricing channel. Under standard models of monopolistic competition with CES, profit margins are unaffected by a demand shock as prices are a fixed function of marginal costs. Given variable markups however, demand declines may induce price reductions which, assuming no concurrent change in marginal costs, would translate to decreases in profit margins.[26]

Our baseline profit margin measure is the ratio of operating profits before interest, taxes, and other extraordinary items to sales. We choose this variable as it is a relatively clean indicator of a firm's ongoing profitability, since it excludes the impact of one-time extraordinary events, funding costs, and changes in tax regimes. Our results are robust to considering alternative definitions of profits such as reported profits after tax (see Table A.3).

[26] Variable markups can be generated under a variety of market structures and assumptions on firm behavior. For a discussion of variable markups under oligopolistic competition, see Edmond et al. (2015) and Gaubert and Itskhoki (2018).

Results from estimating (4) for the baseline profit margin variable are displayed in Table 7, and show that margins are significantly lower for downstream firms post-shock, consistent with the predictions of the pricing channel. As shown in the table, profit margins are 2–3 percentage points higher for upstream firms post-shock. The coefficients are statistically significant and stable in magnitude across fixed effects specifications and after the inclusion of controls. These results represent a numerically meaningful divergence in profit margins after demonetization, as the median profit margin for the sample is 5 percent. These findings suggest that price reductions for consumer facing farms may have played an important role in preventing shock propagation.

5.2 Inventory Stickiness

Frictions in inventory contracts can also diminish the propagation of a demand shock. Firms may hold inventories for a variety of reasons, including ordering related transaction costs, lags in shipping, and demand uncertainty (Alessandria et al. (2010)). Crucially, some of these same factors may contribute to the lack of shock pass-through from downstream to upstream firms. For instance, with non-convex inventory adjustment costs (Khan and Thomas (2007)), retailers facing a temporary demand decline may be disincentived from adjusting their material goods purchases. Similarly, shipping lags may result in retailers having to purchase materials in advance of an unexpected drop in demand. Both factors can create "inventory stickiness", whereby final goods firms' inventory holdings are relatively slow to move in response to a drop in sales.

We proxy for inventory stickiness using a firm's inventory turnover ratio, calculated as sales divided by average inventories. This variable is a standard accounting measure that captures how effective a company is at converting its inventory to sales. Inventory data is only available at a half yearly level, as companies are only required to publish balance sheets at a semi-annual frequency in India. We therefore aggregate sales across (fiscal) quarters and perform inventory analysis at a half-yearly rather than quarterly level. If downstream firms do not fully adjust their inventory holdings in response to demonetization, we would expect inventory turnover to decrease post-shock. Conversely, upstream firms who continue to supply goods to retailers should not see a meaningful change in their turnover ratio.

We show in Table 8 that downstream firms experience a reduction in their inventory turnover ratio post-demonetization, consistent with inventory stickiness predictions. The coefficient on the $Upstreamness \times Post$ interaction remains positive and statistically significant even though we lose observations on account of collapsing the data at a semi-annual frequency. As shown in the table, a one unit increase in ASI and MOSPI upstreamness is associated with a 7% and 3%-5% increase in post-shock inventory turnover. The coefficient remains statistically significant and stable across all our various fixed effects and controls specifications.

A potential competing hypothesis for this result is that downstream firms are more inventory reliant than upstream firms in general, and that demonetization disproportionately affects more inventory reliant industries. If this were the case, then we would naturally expect inventory stickiness to constrain downstream firms more, independent of any supply chain dynamics (Alessandria et al. (2010)). In fact, in our data, upstream firms are more inventory reliant than retailers. The reciprocal of inventory turnover, the inventory to sales ratio, is a widely used proxy for inventory dependence (Gopinath and Neiman (2014)). Its pre-shock value for firms in the lowest upstreamness tercile is 28%, whereas the corresponding number for firms in higher terciles is 33%. These statistics imply that the reduction in inventory turnover for downstream firms is likely not attributable to differences in inventory reliance across the supply chain.

5.3 Exports

A domestic demand shock may also propagate asymmetrically through the supply chain due to the role of exports. Recent literature provides evidence for an "export channel", whereby industries offset local demand declines by boosting exports (Almunia et al. (2020)).

However, relatively less is known about the role of this channel in preventing shock propagation through the supply chain. To demonstrate how this mechanism may work, suppose a small open economy features an entirely non-tradable final goods sector and a completely tradable intermediate goods sector. A demand shock in this case lowers production in the non-tradable sector and marginal costs across both sectors (assuming perfectly mobile local labor markets). In response to this, intermediate goods production may increase, as firms in the sector take advantage of lower marginal costs and export away output that cannot clear the domestic market. In sum, the demand shock will not spread to upstream firms.

The above channel relies on final goods industries being less tradable relative to intermediate goods industries, and indeed we find that this is the case for India. We follow Mian et al. (2020) and classify Agriculture, Forestry and Fishing, Manufacturing, and Mining and Quarrying as tradable industries.[27] Average MOSPI upstreamness for tradable industries is 1.99 whereas that for non-tradable industries is much lower, at 1.34. Since India is a major exporter of services, we define tradability in a more granular way by computing export to value-added ratios across industries (De Gregorio et al. (1994)). As shown in Figure A.3, this ratio increases with higher upstreamness terciles.

To test the relevance of the export channel, we explore heterogeneity in our results by whether a firm is an exporter. We classify a firm as an exporter if its average annual export to sales ratio from 2014-15 is in the top quartile.[28] We then perform a triple difference analysis where we interact $Upstreamness \times Post$ with exporter status. We hypothesize that conditional on upstreamness, exporting firms should see a less steep decline in revenues post-demonetization.[29]

As shown in Table 9, firms defined as exporters have higher revenues post-shock relative to less export intensive firms, even after conditioning on their position in the supply chain. The

[27] The remaining industrial sectors are classified as non-tradable.

[28] Periods refers to fiscal years 2014 and 2015.

[29] A natural alternative specification is to run our standard difference-in-difference with export revenues as the outcome variable. However, we are unable to perform this analysis as few firms in the sample report quarterly export revenues.

coefficient on the $Upstreamness \times Post \times Exporter$ variable is positive across both definitions of upstreamness, though it is only highly statistically significant for MOSPI Upstreamness (as displayed in Panel B). The weaker result for ASI upstreamness is intuitive since we are unable to assign ASI upstreamness for most export intensive industries in agriculture and mining. Even though we lose observations as many firms do not consistently report export revenues, these findings indicate that the relatively higher tradability of intermediate goods may have prevented the complete pass-through of the demonetization shock.

6 Robustness Tests

We vary our research design choices to confirm the robustness of the effects of upstreamness on firm performance. In this section, we describe in detail our additional analyses, which include changes in sample selection, regression specifications, and variable measurement.

Our revenue and wage results are robust to a variety of alternative specifications and variable definitions, as shown in Table 10 and 11, respectively. In both tables, column (1) replicates the baseline coefficients for revenues and wages as reported in column (6) of Table 3 and Table 4, respectively. We first consider whether our results are robust to sample selection. In our main sample, we followed steps to match all firms in the CMIE database that have an identifiable NIC industry code. Thus, for cases where either upstreamness is not available at the five digit level, or where the firm's industry is only reported at levels less granular than five digit industries (i.e. four digit sectors or higher), we impute an industry's upstreamness with the average upstreamness for all five digit industries within the less granular industry sector. We also condition on firms that report outcomes for the twelve quarters between 2015Q1 and 2017Q4. We examine alternatives to these sample selection criteria by considering only firms where the industry (sectors) match exactly with those available in the ASI (MOSPI) and by expanding our sample to an unbalanced panel. Columns (2) and (3) of Table 10 and 11 consider these two alternatives for revenue and wages, respectively. We find that matching on exact industries (sectors), the impact of upstreamness in the periods after demonetization is 3.2-5.6% for revenue and 1.1-3.8% for wages. Expanding the sample to an unbalanced panel gives effects of 2.8-7.5% for revenue and 3.4-3.6% for wages.

The second set of robustness tests varies the structure of our regression specification. Our main results for performance outcomes always include firm fixed effects to control for many company specific time invariant attributes that may affect revenue or wages (e.g. company culture, management). Nevertheless, the regression may be overspecified as the variation we are exploiting comes from differences in upstreamness across industry. In Column (4) of Tables 10 and 11, we repeat the analysis with only industry fixed effects and find that the magnitudes and statistical significance of the difference-in-difference coefficients are similar to the those in our baseline specification. Additionally, we test whether our results are sensitive to the manner in which we include control variables. In our main tests, we fix control variables in the year before demonetization and interact them with the post demonetization indicator. Instead of this approach, in Column (5), we use firm characteristics lagged by a year as time varying control variables and find similar results as before.[30] Finally, in our baseline specification, we employ a method similar to Chodorow-Reich et al. (2019) to strip revenue and wage trends of seasonal patterns. We find that results are robust to using the raw series as outcomes, with the effect of upstreamness on both revenue and wage expense to be slightly larger than baseline.

7 Conclusion

Recent theoretical and empirical work in macroeconomics highlight the role of firms' input-output linkages in transforming local economic shocks into aggregate fluctuations. In this paper, we exploit the 2016 demonetization episode in India—an economically large but initially localized shock to consumer demand—and trace out its effects on firms along the

[30] The age variable is absorbed fully by period fixed effects, and is excluded from this specification.

supply chain. In contrast to previous results in the firm networks literature, we find that the demonetization shock disproportionately negatively affects consumer facing industries and does not meaningfully propagate upstream. We explore pricing power, inventory stickiness, and export capacity as potential "frictions" that may mitigate pass-through of the demonetization induced demand shock and find evidence that all three mechanisms may play a role.

Our analysis of the effects of demonetization have implications for policymakers facing similar shocks to consumer demand, such as the one currently caused by the COVID-19 virus. In particular, governments hoping to mitigate the effects of a demand induced downturn may be well served to target often limited stimulus funds to final goods producing industries, and not necessarily to a broad swath of their economy.

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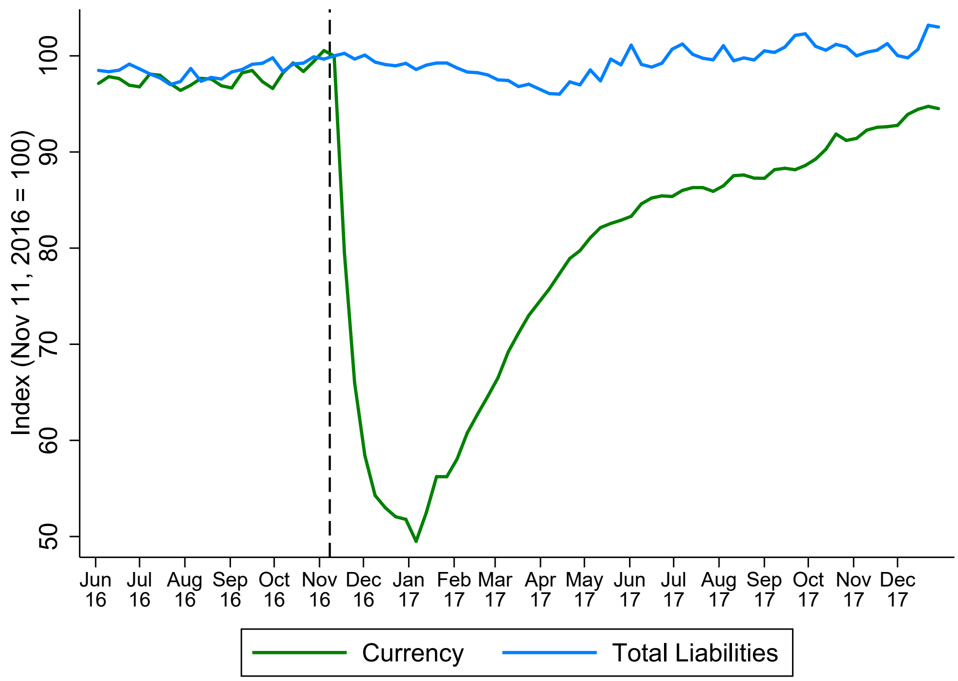
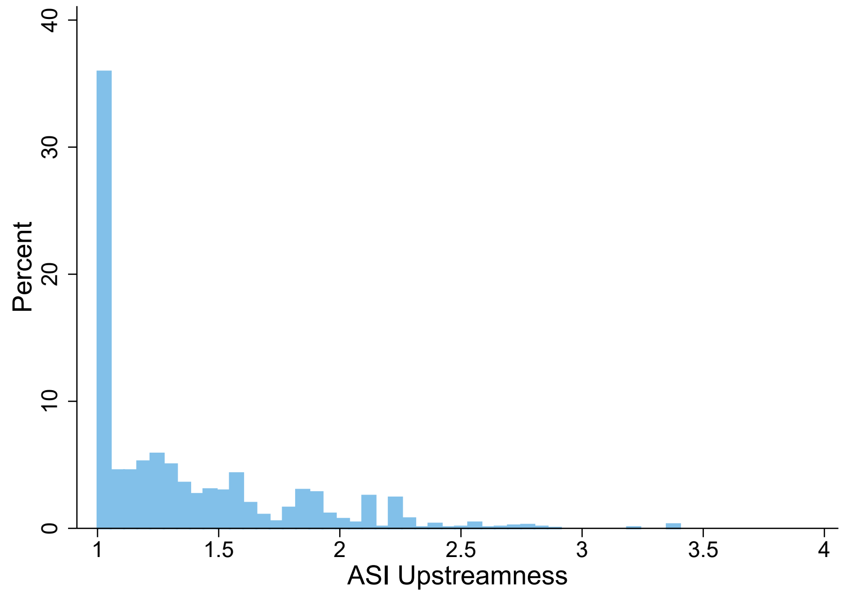
Figure 1: RBI Currency in Circulation & Liabilities

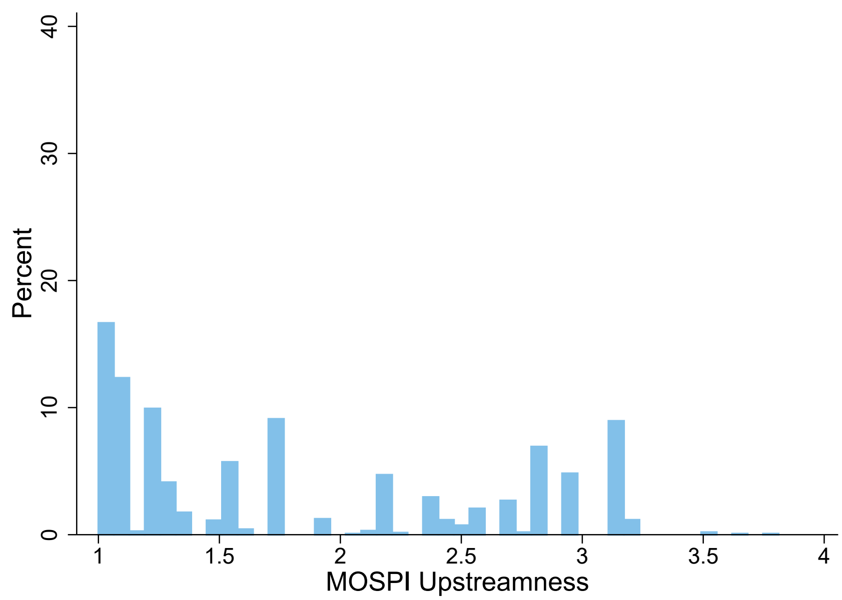


This figure plots the time series for currency in circulation and total RBI liabilities from June 2016 to December 2017. Both currency and liabilities are indexed to their values as of the week ended November 11, 2016. The vertical dashed line indicates the date of demonetization, November 8, 2016. Currency in circulation refers to Item 1.1 in the RBI balance sheet, "Notes in Circulation". Total Liabilities refers to the item "Total Liabilities/Assets" in the RBI balance sheet. The values for currency in circulation and total liabilities as of November 11, 2016 were INR 17,644.51 Bn and INR 32,812.46 Bn, respectively.

Figure 2: Upstreamness Distribution for Sample Firms



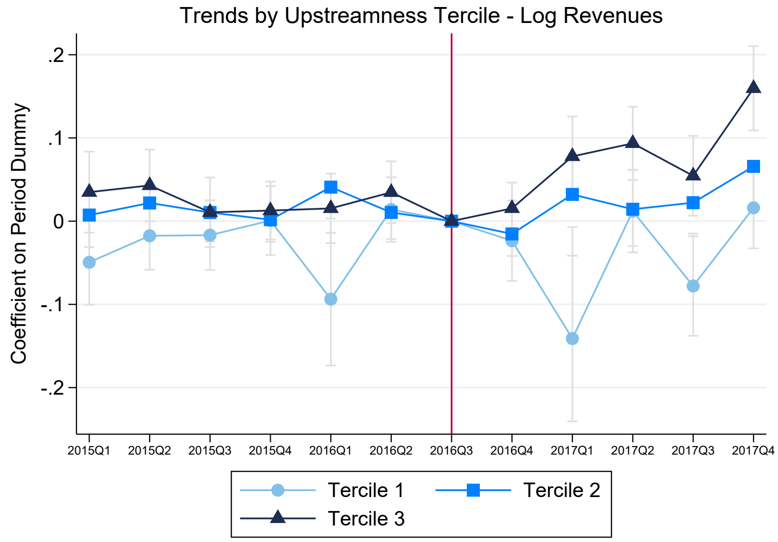
(a) ASI Upstreamness



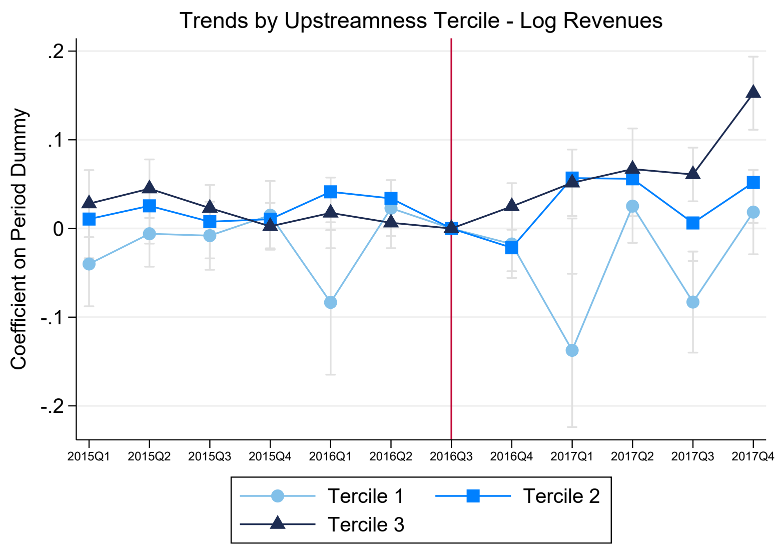
(b) MOSPI Upstreamness

The figure plots the distribution of ASI Upstreamness and MOSPI Upstreamness for sample firms. The sample consists of a balanced panel of firms from Q1, 2015 – Q4, 2017.

Figure 3: Trends by Upstreamness Tercile – Log Revenues



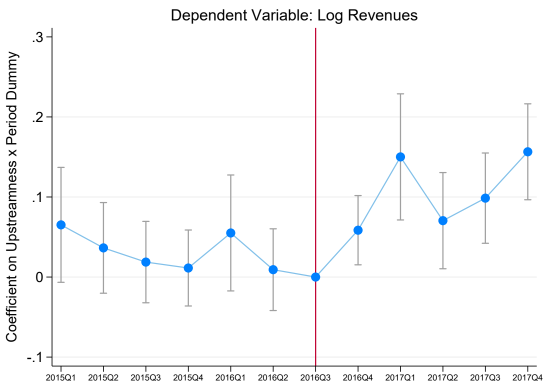
(a) ASI Upstreamness



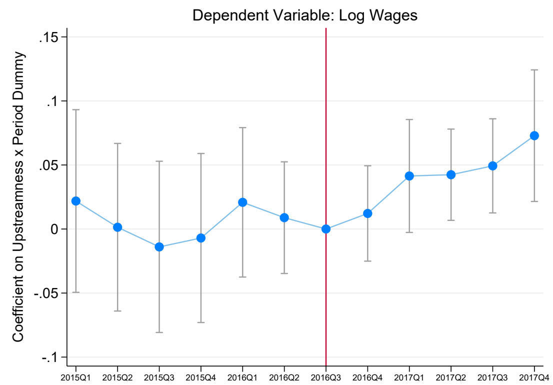
(b) MOSPI Upstreamness

The figure plots average revenues by tercile of upstreamness. Higher terciles indicate higher levels of upstreamness. Sample consists of a balanced panel of firms from 2015-2017. Each point (and the associated 95% confidence intervals) represents the coefficient from regressing revenues on period dummies, after residualizing on firm fixed effects. Standard errors are clustered at the industry level.

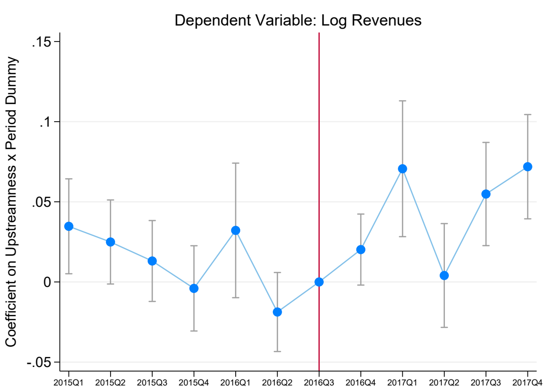
Figure 4: Dynamic Effects of Demonetization



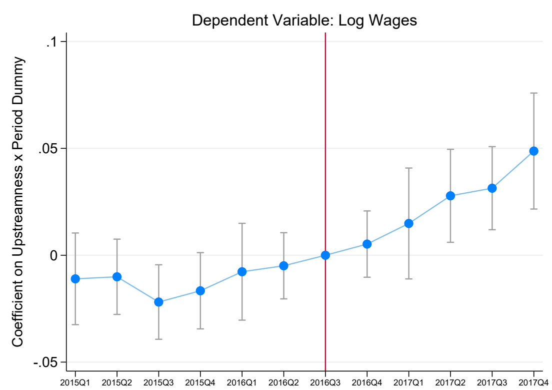
(a) ASI Upstreamness - Revenue



(b) ASI Upstreamness - Wages



(c) MOSPI Upstreamness - Revenue



(d) MOSPI Upstreamness - Wages

The figure plots the β_t coefficients, and associated 95% confidence intervals, from estimating 5 for log revenues and log wages. The period before demonetization, 2016Q3, is the excluded period. Panels (a) and (b) report results for ASI upstreamness, whereas panels (c) and (d) report results for MOSPI Upstreamness. The specification in all panels includes controls, as well as firm and period fixed effects. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period.

Table 1: Summary Statistics

	Upstream Terc. = 1		Upstream Terc. > 1		Total	
	Mean	Median	Mean	Median	Mean	Median
Panel A: Firm Data						
Revenues	1,558.63	247.47	1,896.79	521.83	1,779.98	416.38
Wages	135.51	22.07	149.72	40.63	145.05	35.59
Profit Margin	-0.03	0.04	0.00	0.06	-0.01	0.05
Inventory Turnover Ratio	8.54	3.53	5.27	3.06	6.31	3.13
Capex to Fixed Assets Ratio	0.06	0.02	0.06	0.03	0.06	0.03
Exporter	0.15	0.00	0.27	0.00	0.25	0.00
Leverage	0.22	0.17	0.30	0.28	0.27	0.24
Log Assets	7.22	7.19	7.77	7.66	7.57	7.51
ROA	0.56	0.39	0.67	0.64	0.63	0.53
Age	30.65	27.00	36.16	31.00	34.20	29.00
Firms	912		1,657		2,569	
Panel B: Investment Data						
Project Completion	0.18	0.00	0.19	0.00	0.19	0.00
New Projects	0.09	0.00	0.09	0.00	0.09	0.00
Panel C: Industry Upstreamness						
ASI Upstreamness					1.35	1.22
MOSPI Upstreamness					1.83	1.54

This table presents summary statistics for the outcome and control variables in our analysis. Upstreamness Terc. refers to terciles of MOSPI upstreamness; Terc. = 1 refers to the bottom tercile of upstreamness associated with most consumer facing firms. Sample consists of a balanced panel of firms from 2015-2017. Revenues, wages, and log assets are reported in INR MM. Profit margin is the ratio of operating profits before interest, taxes, and other extraordinary items to sales. Inventory turnover ratio is calculated at a half yearly frequency, and is defined as the ratio of sales to average inventory holdings. Exporter is a binary variable indicating if a firms' average annual export to sales ratio from 2014-15 is in the top quartile of the variable's distribution. Leverage is defined as the ratio of total debt to assets. ROA is calculated as net profit after tax divided by assets. All continuous variables (in levels) are winsorized at the 5% level. Log variables are winsorized at the 1% level. USD 1 = INR 67 as at November 8, 2016 (pre-shock).

Table 2: Non-Parametric Upstreamness and Log Revenues

	Dependent Variable: Log Revenues					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Post	0.006	0.004	–	-0.071	-0.036	–
	(0.012)	(0.013)		(0.046)	(0.047)	
(Upstreamness Terc. = 1) x Post	-0.055**	-0.066***	-0.060**	-0.066***	-0.076***	-0.069***
	(0.023)	(0.025)	(0.024)	(0.021)	(0.022)	(0.023)
Observations	24,183	24,140	24,116	22,706	22,669	22,645
Clusters	368	368		358	358	
Panel B: MOSPI Upstreamness						
Post	0.009	0.010	–	-0.064	-0.031	–
	(0.011)	(0.012)		(0.046)	(0.043)	
(Upstreamness Terc. = 1) x Post	-0.058**	-0.070***	-0.064***	-0.055***	-0.067***	-0.060***
	(0.023)	(0.024)	(0.024)	(0.019)	(0.020)	(0.021)
Observations	28,995	28,935	28,923	27,222	27,169	27,157
Clusters	442	442		428	428	
Firm FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating the following equation:
$y_{fjt} = \beta_1 \mathbb{1}\{Post_t\} + \beta_2(\mathbb{1}\{UpstreamnessTerc. = 1\} \times \mathbb{1}\{Post_t\}) + \delta^T \mathbf{X}_{fjt} + \mu_f + \varepsilon_{fjt}$, where the common variables and indices are exactly as defined in (4). $\mathbb{1}\{UpstreamnessTerc. = 1\}$ is a binary variable that equals one if a firms' industry is in the bottom tercile of the upstreamness distribution. The dependent variable is log revenues (seasonally adjusted). Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3: Upstreamness and Log Revenues

	Dependent Variable: Log Revenues					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.074***	0.080***	0.074***	0.079***	0.083***	0.080***
	(0.025)	(0.026)	(0.026)	(0.022)	(0.024)	(0.024)
Observations	24,183	24,140	24,116	22,706	22,669	22,645
Clusters	368	368	368	358	358	358
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.038***	0.040***	0.040***	0.033***	0.033***	0.032***
	(0.012)	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)
Observations	28,995	28,935	28,923	27,222	27,169	27,157
Clusters	442	442	442	428	428	428
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating equation (4). The dependent variable is log revenues (seasonally adjusted). Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4: Upstreamness and Log Wages

	Dependent Variable: Log Wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.032	0.034	0.032	0.039*	0.042*	0.040
	(0.022)	(0.023)	(0.024)	(0.023)	(0.024)	(0.025)
Observations	23,106	23,100	23,076	21,920	21,914	21,890
Clusters	362	362	362	353	353	353
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.036***	0.037***	0.038***	0.036***	0.037***	0.038***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Observations	27,740	27,732	27,720	26,290	26,282	26,270
Clusters	435	435	435	422	422	422
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating equation (4). The dependent variable is log wages (seasonally adjusted). Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: Upstreamness and Capital Expenditures

Dependent Variable: Capex to Fixed Assets Ratio	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.012**	0.010**	0.010**	0.011**	0.008*	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	11,265	10,980	10,980	10,738	10,492	10,492
Clusters	374	366	366	364	357	357
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.008***	0.006**	0.006**	0.008***	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	13,592	13,252	13,252	12,937	12,650	12,650
Clusters	448	439	439	436	428	428
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating equation (4). The dependent variable is capital expenditure over average net fixed assets. The capital expenditure ratio is calculated at a half yearly frequency, where year refers to fiscal year. Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6: Upstreamness and Project Completion

	Dependent Variable: Project Completion					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.081**	0.089***	0.084**	0.079*	0.080*	0.075*
	(0.035)	(0.033)	(0.035)	(0.044)	(0.042)	(0.045)
Observations	20,452	13,580	13,537	13,587	9,715	9,673
Clusters	2,154	1,381	1,378	1,392	940	936
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.034**	0.030**	0.030**	0.007	0.006	0.001
	(0.014)	(0.012)	(0.012)	(0.016)	(0.014)	(0.014)
Observations	26,885	18,740	18,705	15,321	11,510	11,473
Clusters	2,505	1,717	1,714	1,382	1,018	1,014
Project FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Project x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes
Mean Dep Var	0.178	0.178	0.178	0.178	0.178	0.178

The table presents results from estimating equation (6). The dependent variable is a binary variable indicating whether a project was completed in a particular quarter, conditional on completion by YE 2017. The sample includes only those investment projects that were ongoing as at Jan 1, 2015. Controls include original project cost interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7: Upstreamness and Profit Margins

	Dependent Variable: Profit Margin					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.029***	0.026**	0.023**	0.031***	0.029***	0.026**
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)
Observations	24,504	24,504	24,480	22,992	22,992	22,968
Clusters	368	368	368	358	358	358
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.017***	0.015***	0.016***	0.019***	0.017***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	29,388	29,388	29,376	27,576	27,576	27,564
Clusters	442	442	442	428	428	428
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating equation (4). The dependent variable is profit margin (seasonally adjusted). Profit margin is the ratio of operating profits before interest, taxes, and other extraordinary items to sales. Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8: Upstreamness and Inventory Turnover

	Dependent Variable: Log Inventory Turnover Ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.063*	0.074**	0.074**	0.065**	0.068*	0.068*
	(0.034)	(0.035)	(0.036)	(0.033)	(0.035)	(0.035)
Observations	11,227	11,023	11,023	10,707	10,545	10,545
Clusters	367	367	367	359	359	359
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.029*	0.046***	0.046***	0.033**	0.045***	0.045***
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
Observations	13,317	13,075	13,075	12,709	12,517	12,517
Clusters	435	435	435	425	425	425
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating equation (4). The dependent variable is inventory turnover ratio, defined as the ratio of sales to average inventory holdings. Inventory turnover ratio is calculated at a half yearly frequency, where year refers to fiscal year. Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9: Upstreamness and Log Revenues: Results by Export Intensity

	Dependent Variable: Log Revenues					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post x Exporter	0.083*	0.096*	0.090	0.059	0.077	0.066
	(0.050)	(0.054)	(0.058)	(0.047)	(0.052)	(0.053)
Upstreamness x Post	0.052*	0.050	0.048	0.053*	0.050*	0.052*
	(0.030)	(0.032)	(0.030)	(0.027)	(0.029)	(0.029)
Observations	18,255	18,224	18,164	17,528	17,498	17,438
Clusters	316	316	316	310	310	310
Panel B: MOSPI Upstreamness						
Upstreamness x Post x Exporter	0.079***	0.086***	0.104***	0.057**	0.067***	0.084***
	(0.026)	(0.028)	(0.030)	(0.023)	(0.024)	(0.026)
Upstreamness x Post	0.012	0.007	0.011	0.010	0.004	0.005
	(0.017)	(0.018)	(0.019)	(0.015)	(0.016)	(0.017)
Observations	19,700	19,664	19,616	18,914	18,879	18,831
Clusters	364	364	364	356	356	356
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating the following equation: $y_{fjt} = \beta_1(U_j \times \mathbb{1}\{Post_t\} \times \mathbb{1}\{Exporter_f\}) + \beta_2(U_j \times \mathbb{1}\{Post_t\}) + \delta^T \mathbf{X}_{fjt} + \mu_f + \gamma_t + \varepsilon_{fjt}$, where the common variables and indices are exactly as defined in (4). $\mathbb{1}\{Exporter_f\}$ is a binary variable that equals one if a firms' average annual export to sales ratio from 2014-15 is in the top quartile of the variable's distribution. All fixed effects and controls are interacted with $\mathbb{1}\{Exporter_f\}$. Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 10: Robustness to Alternative Specifications: Revenues

	Dependent Variable: Log Revenues					
	Baseline	Exact Upstreamness Matches	Unbal. Panel	Industry FEs	Parametric Controls	No Season. Adj.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.080***	0.056**	0.075***	0.064**	0.119***	0.076***
	(0.024)	(0.026)	(0.023)	(0.025)	(0.026)	(0.023)
Observations	22,645	14,446	22,678	22,209	23,904	24,192
Clusters	358	227	358	358	365	367
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.032***	0.032***	0.028***	0.034***	0.047***	0.025**
	(0.011)	(0.012)	(0.011)	(0.012)	(0.016)	(0.012)
Observations	27,157	26,209	27,206	26,629	28,716	28,998
Clusters	428	418	428	427	437	439
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Quarter FE	Yes	Yes		Yes	Yes	Yes
State x Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

The table presents results from estimating equation (4). Column (1) replicates the baseline regression results displays in column (6) of Table 3. Column (2) contains only firm-quarters in which the industry match exactly with those available in the ASI or MOSPI. Column (3) expands the sample to an unbalanced panel, allowing firms to enter or exit between 2015Q1-2017Q4. Column (4) employs industry instead of firm fixed effects. Column (5) allows for time varying controls (lagged by a year) instead of non-parametric controls described in Section 3. Finally, in Column (6), the raw series was used as the outcome variable instead of the seasonally adjusted series. The dependent variable is log revenues. Sample consists of a balanced panel of firms from 2015-2017. Unless specified otherwise, controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

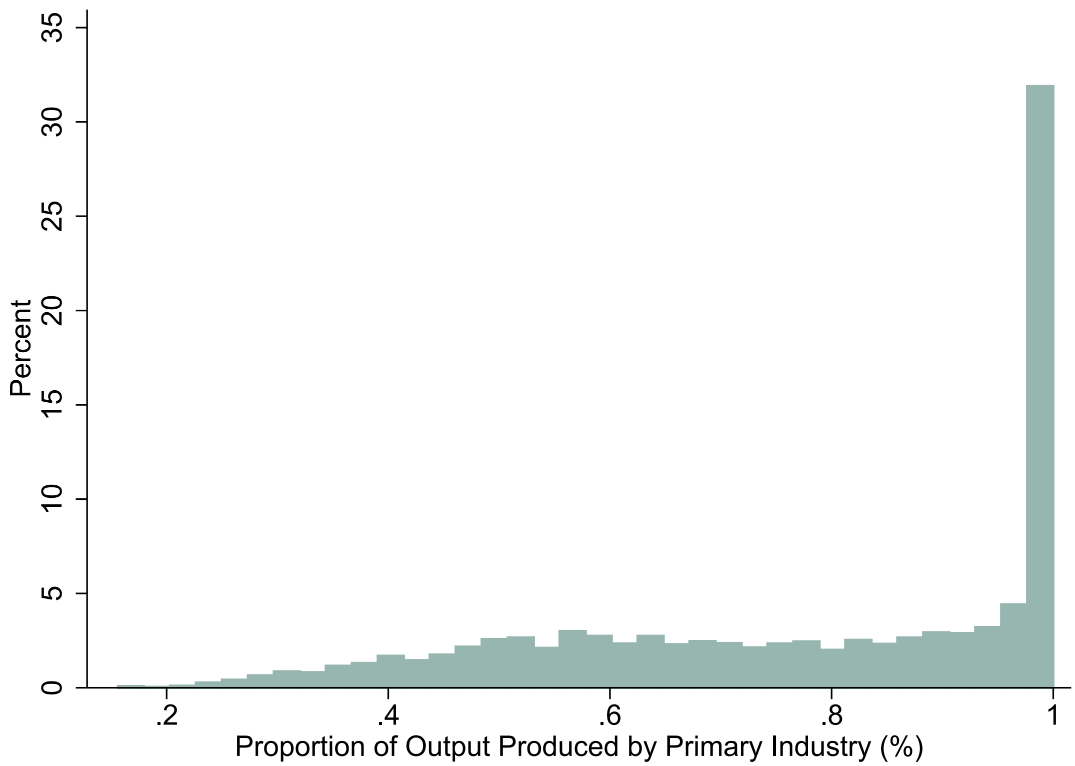
Table 11: Robustness to Alternative Specifications: Wages

	Dependent Variable: Log Wages					
	Baseline	Exact Upstreamness Matches	Unbal. Panel	Industry FEs	Parametric Controls	No Season. Adj.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.040	0.011	0.034	0.031	0.054**	0.040*
	(0.025)	(0.027)	(0.026)	(0.023)	(0.024)	(0.024)
Observations	21,890	14,241	21,896	21,495	22,968	23,365
Clusters	353	225	353	352	361	362
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.038***	0.038***	0.036***	0.038***	0.045***	0.034***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)
Observations	26,270	25,406	26,278	25,798	27,599	28,088
Clusters	422	412	422	420	432	434
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Quarter FE	Yes	Yes		Yes	Yes	Yes
State x Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

The table presents results from estimating equation (4). Column (1) replicates the baseline regression results displays in column (6) of Table 3. Column (2) contains only firm-quarters in which the industry match exactly with those available in the ASI or MOSPI. Column (3) expands the sample to an unbalanced panel, allowing firms to enter or exit between 2015Q1-2017Q4. Column (4) employs industry instead of firm fixed effects. Column (5) allows for time varying controls (lagged by a year) instead of non-parametric controls described in Section 3. Finally, in Column (6), the raw series was used as the outcome variable instead of the seasonally adjusted series. The dependent variable is log wages. Sample consists of a balanced panel of firms from 2015-2017. Unless specified otherwise, controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

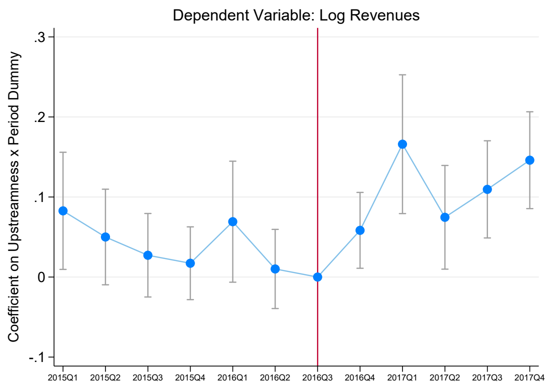
A Additional Figures & Tables

Figure A.1: Output Produced by Primary Industry

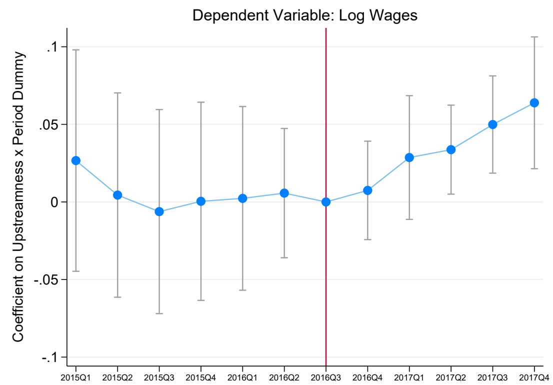


This figure plots the distribution of output produced by a product's primary producing industry in the 2015-16 ASI. A primary producing industry is defined as the industry that produces the greatest fraction of a particular product.

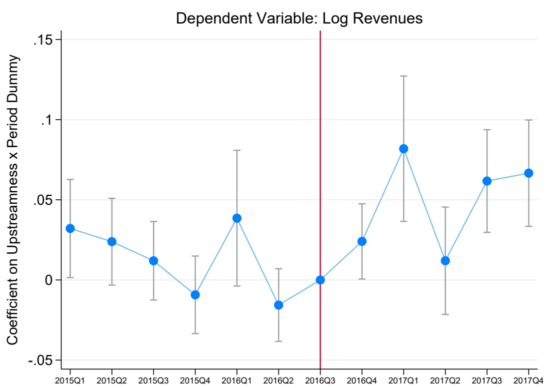
Figure A.2: Dynamic Effects of Demonetization



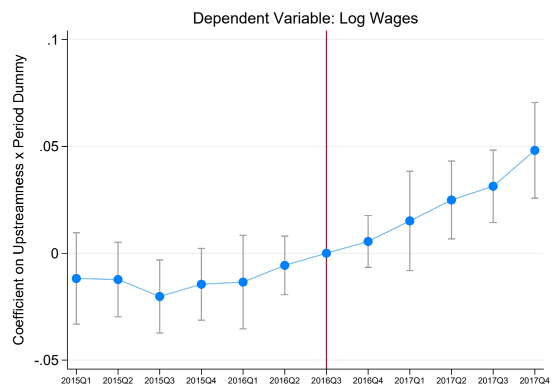
(a) ASI Upstreamness - Revenue



(b) ASI Upstreamness - Wages



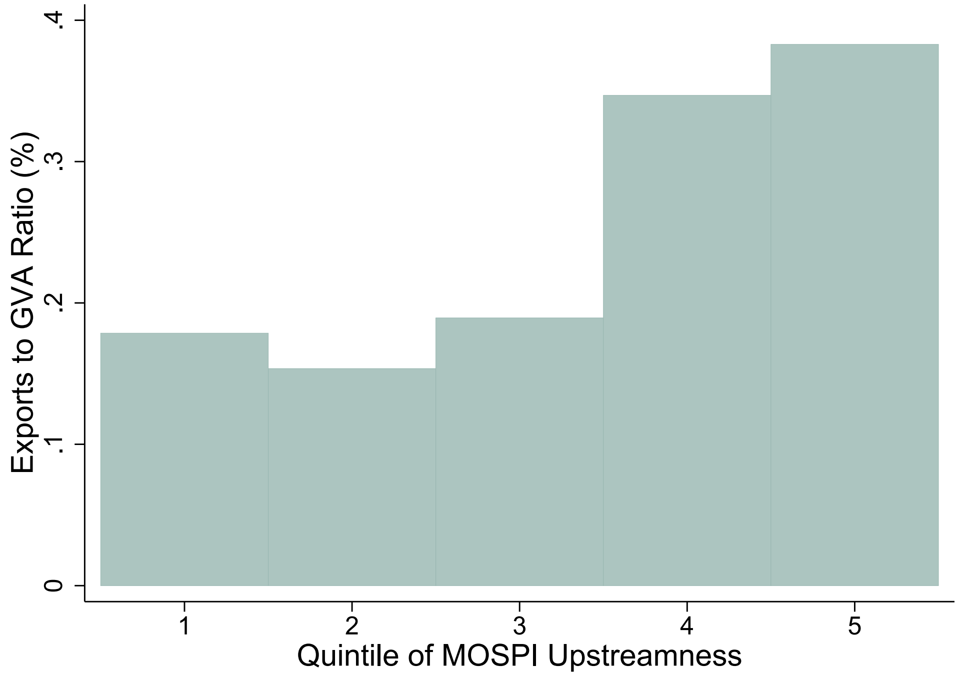
(c) MOSPI Upstreamness - Revenue



(d) MOSPI Upstreamness - Wages

The figure plots the β_t coefficients, and associated 95% confidence intervals, from estimating 5 for log revenues and log wages. The period before demonetization, 2016Q3, is the excluded period. Panels (a) and (b) report results for ASI upstreamness, whereas panels (c) and (d) report results for MOSPI Upstreamness. The specification in all panels includes firm and period fixed effects.

Figure A.3: Export to GVA Ratios by Quintile of Upstreamness



The figure plots the average exports to gross value-added (GVA) ratio by quintile of MOSPI upstreamness, weighted by industry GVA. Data is sourced from the 2015-16 MOSPI Supply Use Tables.

Table A.1: Non-Parametric Upstreamness and Log Wages

	Dependent Variable: Log Wages					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Post	0.001	0.002	–	-0.007	-0.011	–
	(0.007)	(0.007)		(0.030)	(0.034)	
(Upstreamness Terc. = 1) x Post	-0.037**	-0.039**	-0.037**	-0.050**	-0.053**	-0.051**
	(0.016)	(0.016)	(0.016)	(0.022)	(0.022)	(0.021)
Observations	23,106	23,100	23,076	21,920	21,914	21,890
Clusters	362	362		353	353	
Panel B: MOSPI Upstreamness						
Post	0.011	0.015*	–	0.000	0.005	–
	(0.008)	(0.008)		(0.026)	(0.030)	
(Upstreamness Terc. = 1) x Post	-0.057***	-0.060***	-0.057***	-0.066***	-0.070***	-0.068***
	(0.018)	(0.018)	(0.018)	(0.020)	(0.020)	(0.019)
Observations	27,740	27,732	27,720	26,290	26,282	26,270
Clusters	435	435		422	422	
Firm FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating the following equation:
$y_{fjt} = \beta_1 \mathbb{1}\{Post_t\} + \beta_2(\mathbb{1}\{UpstreamnessTerc. = 1\} \times \mathbb{1}\{Post_t\}) + \delta^T \mathbf{X}_{fjt} + \mu_f + \varepsilon_{fjt}$, where the common variables and indices are exactly as defined in (4). $\mathbb{1}\{UpstreamnessTerc. = 1\}$ is a binary variable that equals one if a firms' industry is in the bottom tercile of the upstreamness distribution. The dependent variable is log wages (seasonally adjusted). Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table A.2: Upstreamness and Project Initiation

Dependent Variable: Log New Projects	(1)	(2)	(3)
Upstreamness x Post	0.013	0.016	0.017*
	(0.009)	(0.010)	(0.010)
Observations	51,660	51,660	51,660
Clusters	119	119	119
Firm FE	Yes		
Period FE	Yes	Yes	
Firm x Quarter FE		Yes	Yes
State x Period FE			Yes
Mean Dep Var	0.051	0.051	0.051

The table presents results from estimating equation (4). The dependent variable is log of the sum of new investment projects undertaken by a particular firm in a period. The sample includes only those investment projects that were ongoing as at Jan 1, 2015. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table A.3: Upstreamness and Reported Profit Margins

	Dependent Variable: Reported Profit Margin					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: ASI Upstreamness						
Upstreamness x Post	0.128**	0.126**	0.127**	0.146***	0.140**	0.143***
	(0.051)	(0.052)	(0.052)	(0.055)	(0.056)	(0.055)
Observations	24,492	24,492	24,468	22,980	22,980	22,956
Clusters	368	368	368	358	358	358
Panel B: MOSPI Upstreamness						
Upstreamness x Post	0.076**	0.072**	0.073**	0.096***	0.090***	0.090***
	(0.032)	(0.032)	(0.032)	(0.034)	(0.035)	(0.035)
Observations	29,376	29,376	29,364	27,564	27,564	27,552
Clusters	442	442	442	428	428	428
Firm FE	Yes			Yes		
Period FE	Yes	Yes		Yes	Yes	
Firm x Quarter FE		Yes	Yes		Yes	Yes
State x Period FE			Yes			Yes
Controls				Yes	Yes	Yes

The table presents results from estimating equation (4). The dependent variable is reported profit margin (seasonally adjusted). Reported profit margin is the ratio of reported profit after tax to sales. Sample consists of a balanced panel of firms from 2015-2017. Controls include leverage, log assets, ROA, and firm age as at 2016 Q3 interacted with period. Robust standard errors (reported in parentheses) are clustered at the industry level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

B Variable Definitions

Variable	Definition
A. Firm Data	
Revenues	Quarterly revenues (siq_ntrm_net_sales).
Wages	Quarterly wages (siq_ntrm_wages_salaries).
Profit Margin	Ratio of operating profits before interest, taxes, and other extraordinary items (siq_ntrm_pbit_net_of_peoi) to revenues (siq_ntrm_net_sales).
Capital Expenditure Ratio	Ratio of fiscal half yearly capital expenditure to average net fixed assets. Capital expenditure is calculated as $FA_t - FA_{t-1} + Dep_t$ where t and $t-1$ represent current and previous fiscal half year, respectively. FA indicates net fixed assets (e.g. property, plant, and equipment) and Dep indicates depreciation expense (siq_depreciation). Average net fixed assets is calculated as average of net fixed assets (siq_ntrm_net_fixed_assets) in the current and previous fiscal half year.
Inventory Turnover Ratio	Ratio of fiscal half yearly sales to average inventory holdings. Fiscal half yearly sales calculated as the sum of revenues for a fiscal half. Average inventories is calculated as average of inventories (siq_ntrm_inventories) as at fiscal half start and inventories as at fiscal year end.
Exporter	Binary variable indicating if a firm's average annual export to sales ratio from 2014-15 is in the top quartile of the variable's distribution.
Leverage	Ratio of total debt (siq_ntrm_borrowings) to total assets. Total assets is calculated as the sum of net fixed assets (ntrm_net_fixed_assets), investments (siq_ntrm_investments), other non current assets (siq_ntrm_other_non_current_assets), current assets (siq_ntrm_curr_assets_loans_n_advns), capital work in progress (siq_ntrm_cap_work_in_progress), net pre-operative expenses (siq_ntrm_net_pre_operative_exp), other assets (siq_ntrm_other_assets), deferred tax assets (siq_ntrm_deferred_tax_asst), and miscellaneous expenses not written off (siq_ntrm_misc_exp_not_written_off).
Log Assets	Log of total assets.
ROA	Return on assets, calculated as net profit after tax (siq_ntrm_pat) divided by total assets.

Variable	Definition
Age	Calendar year of reporting minus firm incorporation year (incorporation_year).
Reported Profit Margin	Ratio of reported profit after tax (siq_ntrm_reported_pat) to revenues (siq_ntrm_net_sales).
B. Investment Data	
Project Completion	Binary variable indicating whether a project was completed in a particular quarter, conditional on completion by YE 2017. A project is identified as being completed in a quarter if its project status (Project Status) is categorized as "Completed".
New Projects	Sum of new investment projects undertaken by a particular firm in a period.
C. Industry Upstreamness	
ASI Upstreamness	Upstreamness calculated from constructed input-output table from the 2015-16 survey round of the Indian Annual Survey of Industries. See Section 2.4 for more details.
MOSPI Upstreamness	Upstreamness calculated from 2015-16 official supply use tables (SUT 2015-16) published by the Indian Ministry of Statistics and Programme Implementation (MOSPI). Available at http://mospi.nic.in/publication/supply-use-tables.