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Supply Chain Networks and the Macroeconomic Expectations of Firms*

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Abstract

In a randomized control trial of customer-supplier firm pairs in New Zealand, we treat with information one firm in a pair and analyze the treatment's effects on the expectations and actions of both the directly treated firms (direct effect) and connected firms that did not directly receive information (spillover effect). The direct and spillover effects on expectations and actions are significant and of comparable magnitude. Higher expected future real GDP growth increases prices and employment, while greater uncertainty about it reduces prices, investment, and employment. We show that spillover effects on the connected firms' expectations are driven by inter-firm communication, as opposed to observable actions. This matters as we find communication to be symmetric upstream vs downstream, while propagation via actions is asymmetric. We embed inter-firm communication along the supply chain in a New Keynesian pricing problem and discuss implications for the transmission of aggregate uncertainty to prices and inflation.

JEL codes: D8, E3, E4, E5, L14

Keywords: Communication, Firms, Macroeconomic Expectations, Networks, Spillovers

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1 Introduction

Macroeconomic expectations are a key driver of aggregate dynamics (Beaudry and Portier, 2006, 2007; Jaimovich and Rebelo, 2009). Empirical research over the past decade has intensified the analysis of uncovering how these expectations are formed (Coibion and Gorodnichenko, 2015; Coibion, Gorodnichenko, and Kamdar, 2018), and what their effect is on individual decision-making (Coibion, Gorodnichenko, and Ropele, 2020; Georgarakos et al., 2024). Special interest has been placed on firms' decision-making given their price-setting power (Coibion, Gorodnichenko, and Kumar, 2018; Coibion et al., 2020), and the influence of aggregate uncertainty in shaping these decisions (Bloom, Bond, and Van Reenen, 2007; Bloom, 2009; Coibion et al., 2024; Kumar, Gorodnichenko, and Coibion, 2023).

The interdependence of beliefs between firms is thought to play a key role, for example, being at the foundation of sentiment-driven business cycles (Angeletos and La'O, 2013; Gaballo, 2018). Motivated by supply chain interactions being fundamental to shock propagation and amplification (Acemoglu et al., 2012; Acemoglu, Akcigit, and Kerr, 2016; Carvalho et al., 2021; Ozdagli and Weber, 2023; Pasten, Schoenle, and Weber, 2020), we investigate *how a firm's supply chain shapes its macroeconomic expectations, and the consequences for its decision-making*. We provide experimental evidence on the presence and relevance of information diffusion between firms, and reveal direct communication to be a central, yet unexplored, mechanism. Unlike standard shock propagation via prices or output being asymmetric upstream vs downstream (Acemoglu, Akcigit, and Kerr, 2016; Carvalho and Tahbaz-Salehi, 2019), we find communication to be symmetric. This potentially reconfigures our understanding of how shocks propagate through supply chains, and we embed communication into a macroeconomic model to explore its aggregate consequences.

To proceed, we surveyed approximately 1,000 firm-firm pairs in New Zealand, with one firm being the primary supplier of the other. We incorporated a randomized controlled trial (RCT) using an information-based treatment of official forecasts of GDP growth. We had two treatment groups, one receiving the mean of the forecasts and the other receiving the range across forecasts, in order to assess the impact of uncertainty. Importantly, in each treated pair, only one firm receives the information (either the supplier or the customer in the relationship, chosen at random). This design therefore allows us to identify both the *direct effect* of receiving macroeconomic information on the "main" firm that the treatment was applied to, and the *spillover effect* on the "connected" firm in the same pair that did not directly receive the treatment. The survey consists of two waves (baseline and follow-up), and information is provided at the end of the baseline. The follow-up takes place three months later, allowing us to identify the diffusion of macroeconomic information between a firm and its supplier or customer, and to measure the effects on real decisions.

The provision of information caused *both* the main and the connected firms to update their expectations. The direct effect on the main firms corroborates findings in the literature (Coibion, Gorodnichenko, and Kumar, 2018; Kumar, Gorodnichenko, and Coibion, 2023).[1] The spillover effects on the connected firms, however, are new. As expected, the connected firms' expectations show a change only in the follow-up period, not in the baseline period, consistent with it taking time for the information to diffuse. Interestingly, the spillover effects are large, with their magnitude being comparable to that of the direct effects, implying that the information diffusion is strong.

Analyzing the impact of our information treatment on firms' decisions (actions)—prices, investment, employment, and wages—we find significant effects in the follow-up of the directly treated *and* connected firms, both with similar magnitudes. Using variation induced by the treatment to instrument firms' GDP growth expectations, we find that a 1 percentage point increase in expected GDP growth increases firms' prices by 0.28 percentage points and employment by 0.92 percentage points, compared to their plan three months ago. We find that a 1 percentage point increase in uncertainty, measured as the distance between the most and least likely GDP growth scenario, decreases prices by 0.31 percentage points, in-

[1] Despite the official forecasts being public information, the inattention of firms with respect to this information is well-established, both in our setting (see Coibion, Gorodnichenko, and Kumar, 2018) and more generally (Candia, Coibion, and Gorodnichenko, 2024; Song and Stern, 2024). For theoretical mechanisms rationalizing this inattention, see, for instance, Afrouzi and Yang (2018); Gabaix (2020); Sims (2003).

vestment by 0.63 percentage points, and employment by 0.79 percentage points, compared to their plans three months ago. We find no effect on wages from either the mean or the uncertainty treatments.

The significant shift in expectations and decisions of connected firms suggests that the supply chain network is a highly relevant source of information for macroeconomic expectations and decisions, with meaningful interactions and information spillovers between connected firms. Next, we assess the potential mechanisms underlying this information diffusion. Specifically, we want to disentangle whether communication between firms, or inference from changes in observable actions of the other firm, can explain the learning we find. We offer a number of pieces of evidence suggesting that communication is important.

First, we decompose the spillover effect on a connected firm's posterior beliefs into the impact coming from the main firm's posterior beliefs as opposed to the main firm's actions. We find only the former to be significant, suggesting that connected firms form their beliefs by directly learning the main firm's beliefs, conceivably through communication. Second, in the survey, we asked the firms directly about their GDP communication within the pair. We find a large and statistically significant effect: 85% (73%) of mean (uncertainty) treated firms reported communicating, compared to only 35% of control firms.

Third, we show that the spillover effects are symmetric whether flowing upstream or downstream (the main firm is a customer or supplier in the pair, respectively). If learning were mediated exclusively through observing the actions of the main firms, one would expect asymmetric treatment effects, as the literature has documented that shocks tend to propagate via prices or output more in one direction (Acemoglu, Akcigit, and Kerr, 2016; Carvalho and Tahbaz-Salehi, 2019). Conversely, using our survey question on GDP communication, we find that the effect on communication from treatment is the same whether the main firm is the customer or supplier in the pair, a finding that is consistent with the treatment effect on expectations and actions being symmetric.

We end the paper by investigating the implications of our findings in a New Keynesian pricing problem, where aggregate output (GDP) growth is exogenously given. Building on the pricing block of the production network model in Rubbo

(2023), we incorporate a communication network that firms utilize when forming their expectations about output growth, the latter being imperfectly observed by firms. Motivated by our empirical findings, we assume that the communication network is symmetric (equal communication upstream and downstream) and that firms are ambiguity-averse, as a tractable way for uncertainty to be relevant for decisions despite the fact that we log-linearize the model (Ilut and Schneider, 2014).[2] Our setup allows us to show that, in equilibrium, firms' pricing decisions are influenced by both the production and the communication networks. Consistent with our empirical evidence, the model implies a negative response of firms' prices to a treatment of higher uncertainty about future output growth.

We characterize the implications of communication using the model both theoretically and quantitatively. For the latter, we parameterize the model to closely match key components of firms in our survey data and simulate outcomes when a subset of firms is given information about higher uncertainty about future output growth. Our analysis yields three key insights. First, whether the treatment was provided to the supplier or the customer firm does not matter for its impact on all firms' prices when firms communicate, highlighting that communication generates symmetry in upstream vs downstream transmission of a treatment.

Second, communication reduces the dispersion of price response to a treatment across firms when compared to no communication. We empirically validate this result of the model by computing the connected firm's price change associated with a 1 percentage point exogenous increase in the treated firm's price in our model simulations and survey data. We show that when there is communication, the estimated price relationship between the treated and connected firm approaches unity both empirically and in the model, regardless of whether the treatment was provided to a customer or supplier firm.

Third, communication results in a stronger and shorter-lived response of inflation to future output growth uncertainty, consistent with communication both propagating and homogenizing the initial price response of most firms, relative to

[2]Ambiguity-aversion refers to Knightian uncertainty whereby firms cannot assess the probability distribution of outcomes accurately. See Epstein and Wang (1994) for an early application of such uncertainty to asset pricing and Ilut and Schneider (2023) for a recent review.

no communication. Moreover, the response of the aggregate price level to future output growth uncertainty is, on average, higher when firms communicate with one another compared to when they do not. The result that communication generates symmetry in the transmission of shocks upstream and downstream for firms' prices carries over to the aggregate price level and inflation, too.

Our empirical findings and results from the model suggest that inter-firm communication is an important transmission mechanism through which firm-specific idiosyncratic shocks propagate. The key macroeconomic implication of the model is that, in response to a shock about future aggregate uncertainty (received by a subset of firms), communication can amplify the response of aggregate inflation on impact while mitigating its persistence. Furthermore, our findings underscore the importance of accounting for production and communication networks, and their influence on expectations when estimating structural parameters in crucial macroeconomic equations, such as the Phillips curve. Finally, our result that communication helps propagate firms' macroeconomic expectations on the production network can provide insights into the design of alternative policy communication strategies. For example, policymakers can anchor firms' expectations by focusing their policy communication efforts on firms that communicate with many other firms in the production network.

The key contribution of this paper is experimental evidence on information diffusion between firms shaping their macroeconomic expectations. This question has roots in the information "island" models initiated by Lucas Jr (1972), with Andrade et al. (2022) providing evidence that firms' inflation expectations are related to their industry conditions, and Albagli, Grigoli, and Luttini (2022) that they are related to their supplier prices. Coibion et al. (2021) and Kieren et al. (2025) present evidence of higher-order inflation expectations between firms. Sebbesen and Oberhofer (2024) document aggregate dependence of firm output expectations between markets linked through intermediate goods trade.[3] Our application

[3]Our work is more broadly related to the research on households forming macroeconomic expectations through social networks, such as for inflation (Garcia-Lembergman et al., 2024; van Rooij et al., 2024), and for the housing market (Bailey et al., 2018), and even more broadly to the networks literature on social learning (Bramoullé, Galeotti, and Rogers, 2016; Jackson, 2008).

of experimental methods to the spillover effects of macroeconomic information treatments on firms pioneers a shift in the recent and rapidly growing literature confined to direct effects (Abberger et al., 2024; Coibion, Gorodnichenko, and Kumar, 2018; Coibion et al., 2020; Coibion, Gorodnichenko, and Ropele, 2020; Coibion and Gorodnichenko, 2025; Kumar, Gorodnichenko, and Coibion, 2023).

Our findings support the recent quantitative literature that models and emphasizes the macroeconomic implications of a firm's belief formation interacting with the production network, by offering experimental validation of this interaction. Fang et al. (2024); Jamilov et al. (2024) consider optimal attention toward other firms in the network, and Afrouzi (2024) toward competitors. Bui et al. (2022), Chahrour, Nimark, and Pitschner (2021), and Pellet and Tahbaz-Salehi (2023) incorporate higher order expectations along the supply chain. Nikolakoudis (2024) allows beliefs to incorporate information inferred from supplier prices.

We uncover communication to be a new mechanism for the transmission of economic shocks along supply chains, contributing to the wide literature on this subject (Acemoglu et al., 2012; Acemoglu and Tahbaz-Salehi, 2025; Baqaee and Farhi, 2019; Barrot and Sauvagnat, 2016; Bigio and La'O, 2020; Carvalho and Tahbaz-Salehi, 2019; Carvalho et al., 2021). Of particular relevance are those works analyzing monetary policy, given our focus on macroeconomic expectations (Cox et al., 2024; Ghassibe, 2021; La'O and Tahbaz-Salehi, 2022; Pasten, Schoenle, and Weber, 2020; Rubbo, 2023). Our findings offer qualitatively distinct theoretical implications as the communication network implies symmetry in upstream vs downstream transmission, while standard propagation via prices or output is asymmetric (Carvalho and Tahbaz-Salehi, 2019).

The rest of the paper is organized as follows. Section 2 discusses the experimental design and data. Section 3 presents the estimation, with the treatment effects on beliefs in Section 3.1 and on actions in 3.2, for both the main and the connected firms. Section 4 presents evidence for communication between firms driving the information diffusion. Section 5 introduces communication in a production network model and analyzes its macroeconomic implications. Section 6 concludes.

2 Survey and Experimental Design

We designed and administered a two-wave field survey of firm managers. We conducted a randomized control trial utilizing an information-based treatment, building on the design in Kumar, Gorodnichenko, and Coibion (2023). The key novelty of our design is that we observe and exploit the supply chain connections between firms. Specifically, our sample consists of pairs of firms where one is the primary supplier of the other (according to expenditure share on intermediates).

The survey was conducted by New Zealand Market Research and Surveys Limited. This company surveys firms and records information about their business operations, including, importantly, who their primary supplier is. This allowed us to identify pairs of firms and ensure that the primary supplier in one pair is not the customer firm in another pair to minimize control contamination. These firms are mostly in the manufacturing and trade sectors, employ at least three workers, and have an annual sales turnover of at least NZL $30,000. The survey company holds contact details for approximately 8,100 pairs of firms. Upon contacting all of them, 1,074 pairs agreed to participate in the survey (a 13 percent response rate at the pair level). Each firm in the pair was not informed of the other's participation. The survey was conducted mostly by telephone, with around 15 percent participating via an online platform.[4] The survey respondent was the firm manager who is involved in the firm's pricing decisions.

The set of firms in the survey company's dataset is representative of the population of firms in New Zealand in terms of industry and employment size. This is less the case in our sample due to the variation in response rates across firms. A key challenge in firm surveys is ensuring a high enough overall response rate, which is more severe in our setting given that we need both firms in a pair to participate; we therefore prioritized this at the expense of representation. With the assistance of survey recruitment specialists, we ensured that nearly half of this sample of pairs participated in both waves. These statistics are similar to those

[4] Data research assistants asked questions directly from our questionnaire. The responses were recorded in hard-copy form and later digitized. Different groups of data research assistants were employed to perform specific tasks to maintain the quality of the survey.

in Kumar, Gorodnichenko, and Coibion (2023), despite them not requiring pairs. Details on our sample are reported in Table A-1 and the Online Appendix C.1.

The survey consisted of two waves: the *baseline* and the *follow-up*. The baseline wave was conducted between July and October 2024, and the follow-up wave was conducted between October 2024 and January 2025. The time elapsed between waves for any given firm was ensured to be about three months. Moreover, both firms within a pair were surveyed within approximately three days of one another, to minimize possible contamination (e.g., interaction between the firms before the baseline of both firms was complete). The information treatment was applied in the baseline survey, and the three-month duration until the follow-up survey was chosen to allow sufficient time for the potential diffusion of information within the pair.

We applied the treatment at the firm-pair level, with only one firm out of the pair directly receiving the treatment. We refer to the directly treated firm as the *main* firm, and the other (indirectly treated) firm as the *connected* firm. The main firm within the pair was chosen randomly, conditional on treatment group, so that we could assess the diffusion of information both upstream and downstream in the supply chain. Pairs were randomly assigned to one of three groups. The first group, treatment 1, received information about the first moment of future GDP growth (the average forecast for GDP in 2025). The second group, treatment 2, received information about the second moment of future GDP growth (the range of forecasts for GDP in 2025). The third group, the control, received no information. The exact text given in the two treatments was as follows:

1. Treatment 1 (Mean). *We are going to give you information from a group of leading experts about the New Zealand economy. According to Consensus Economics, a leading professional forecaster, the average prediction among professional forecasters is that the real GDP will grow by 2.3% in 2025.*

2. Treatment 2 (Uncertainty). *We are going to give you information from a group of leading experts about the New Zealand economy. According to Consensus Economics, a leading professional forecaster, the difference between the lowest and highest predictions of real GDP growth is 2.2 percentage points for 2025.*

We identify the direct and spillover effects using the variation visualized in Figure 1. The information on GDP forecasts is given to the main firm of the treated pair. We compare the responses given by the main (connected) firm in the treated pair to the main (connected) firm in the control pair to identify the direct (spillover) effects of the treatment. Under the assumption of no interference between pairs[5] — i.e., no effect of treatment between pairs — identification of the direct (spillover) effects follows from the random assignment of treatment to pairs, as the control main (connected) firm is a valid counterfactual for the treated main (connected) firm.[6] By organizing the experiment at the pair level in this way, an important strength of our design is that it avoids the complexities often inherent in settings of network interference (Aronow and Samii, 2017; Liu and Hudgens, 2014).

In the baseline wave, we asked questions about the firm's own characteristics (age, employment, revenue, labor/material share of costs, market share, and frequency of price changes), manager characteristics (tenure and education), planned changes in actions over the next three months (prices, investment, employment, and wages) and beliefs about future GDP growth (mean and range). The exact text given regarding their beliefs is as follows:

1. Beliefs about the mean. *What do you think will be the annual growth rate of real GDP in New Zealand in twelve months? Answer: ________ % per year.*

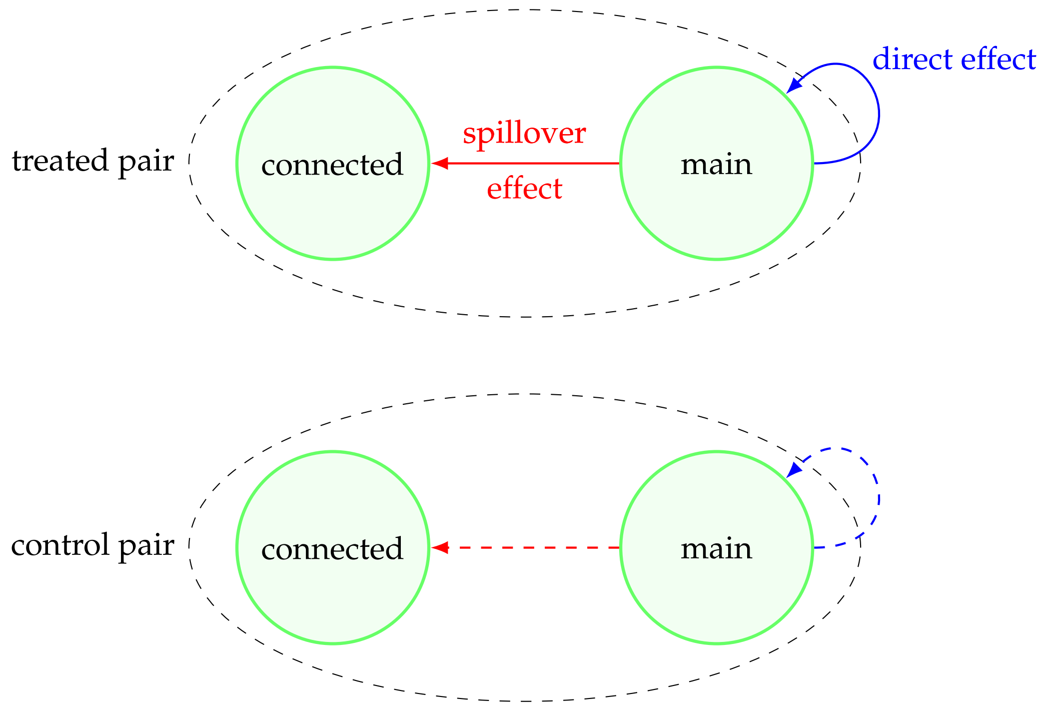
2. Beliefs about uncertainty. *Could you provide us with an approximate range of what you think annualized real GDP growth in New Zealand will be over the next 12 months? Answer: between ________ % per year (lowest forecast) and ________ % per year (highest forecast).*

We asked about their beliefs twice, before and after treatment. The latter allows

[5] Recall, this is minimized by choosing pairs such that the main firm in one pair is not the primary supplier of the connected firm in another pair. Nonetheless, violation of this assumption would likely only attenuate our treatment effects under the reasonable assumption that spillover effects are less between than within pairs.

[6] Control pairs are required, rather than single firms, because main and connected firms are not comparable (only one is guaranteed to be the primary supplier of another firm). Hence, identification only follows from comparing main to main and connected to connected between treated and control. See Pollmann (2023) for details in a spatial context.

Figure 1: Research Design Visualization



us to identify the instantaneous effect of the treatment on their beliefs. All other questions were asked before the treatment. Importantly in this wave, we did not ask anything about their supply chain in order to avoid priming the firms to share the information.

In the follow-up wave, we asked what their beliefs about future GDP growth are (same wording as in the baseline), how they changed their actions over the past three months, questions about what is driving their beliefs (including sources of information and communication with the connected firm), and supply chain information (expenditure/sales share and pricing contracts with the connected firm). The reported beliefs in this wave allow us to identify the persistent effect of the treatment on the main firm, and whether there was any diffusion to connected firms. Moreover, we compare their actual change in actions vs planned change in order to determine if any belief change translates to real effects on decision-making. See the Online Appendix D for the complete survey.

Online Appendix Table A-2 shows that the treatment assignment is balanced among the available characteristics of the firms, other than treated firms being slightly younger on average. Additionally, while all 1,074 pairs of firms were contacted for the follow-up, only 539 pairs of firms participated, because either one or both firms in the pairs did not answer the survey. Online Appendix Table A-3 shows that neither the treatment assignment nor the observable characteristics can predict participation in the follow-up survey.

3 Treatment Effects

3.1 Treatment Effects on Expectations

We start by evaluating whether our treatments affected firms' GDP expectations. To do so, we compare how treated and control firms changed their posterior GDP expectations relative to their prior GDP expectations. Specifically, we run the following regression, which is widely used in this type of setting (see, for example, Coibion, Gorodnichenko, and Kumar, 2018; Kumar, Gorodnichenko, and Coibion, 2023)[7]:

$$Posterior_i^{mean} = \alpha + \beta Prior_i^{mean} + \sum_{n=1}^{2} \gamma_n T_{n,i} + \sum_{n=1}^{2} \theta_n Prior_i^{mean} \times T_{n,i} + \varepsilon_i, \quad (1)$$

where $Prior_i^{mean}$ is the belief of firm i's manager about the mean of GDP growth in the baseline period before the treatment intervention. $Posterior_i^{mean}$ is the belief after the treatment intervention. We use two measures of posterior beliefs. The first is an instantaneous measure, asked immediately after the treatment intervention in the baseline, and the second is a persistent measure, asked in the follow-up three months after the baseline. $T_{n,i}$ is a dummy that takes a value of 1 if firm i is in a pair that received treatment n ($n = 1$ is mean, $n = 2$ is uncertainty) and 0 otherwise.

[7] Some of these papers also employ Huber-robust regressions, which increase power by down-weighting observations with large residuals, typically those with substantial prior-posterior revisions.The findings remain qualitatively unchanged and, if anything, become quantitatively stronger.

We run the regression separately for the main firms in order to estimate the direct effect, and separately for the connected firms in order to estimate the spillover effects (corresponding to Figure 1). Note that the treatment status $T_{n,i}$ is the same for both main and connected firms within the same pair; that is, a connected firm is treated if the main firm it is paired with is also treated. We also rerun the regression for the posterior and prior on uncertainty, rather than the mean.

The coefficient β captures the correlation between prior and posterior for the control group. As the control received no information, we expect that β is close to one. $\beta + \theta_n$ captures the correlation between prior and posterior for treated group n. If treatment n is effective, we will see changes in expectations such that treated firms place some positive weight on the new information. Consequently, θ_n will be negative, as the correlation between the prior and posterior would be lower than in the control group. Because the treatment is randomized, we can interpret θ_n as the causal effect of information on the prior-posterior correlation. γ_n is the the causal effect when prior expectations equal zero (the y-intercept), which we expect to be positive if the correlation (the slope) decreases. Visually, the relationship between the posterior and prior rotates clockwise due to treatment (see Figure 2).

We present the results on the beliefs of mean GDP growth in Table 1. Columns (1) and (2) show the treatment effects in the baseline period for the main and connected firms, respectively. Columns (3) and (4) show the treatment effects in the follow-up period for the main and connected firms, respectively. Figure 2 presents the corresponding distributions of posterior against prior beliefs in the four cases. As expected, the estimated correlation between the prior and posterior for the control group, β, is close to one across all four specifications in Table 1, and the distribution along the 45-degree line in Figure 2, indicating no systematic change in the control firms' beliefs before or after treatment.

The treatment effect on the main firm — the direct effect — in the baseline period (Column 1) from treatment one (provision of the mean official forecast of GDP growth) is $\theta_1 = -0.723$, a reduction in correlation of approximately three-quarters relative to the control firms. Firms directly receiving the information, therefore, immediately update their priors. Treatment two (provision of the range of official GDP growth forecasts) also leads to a significant reduction in correlation, though

Table 1: Treatment Effect on GDP Expectations in Baseline and Follow-up

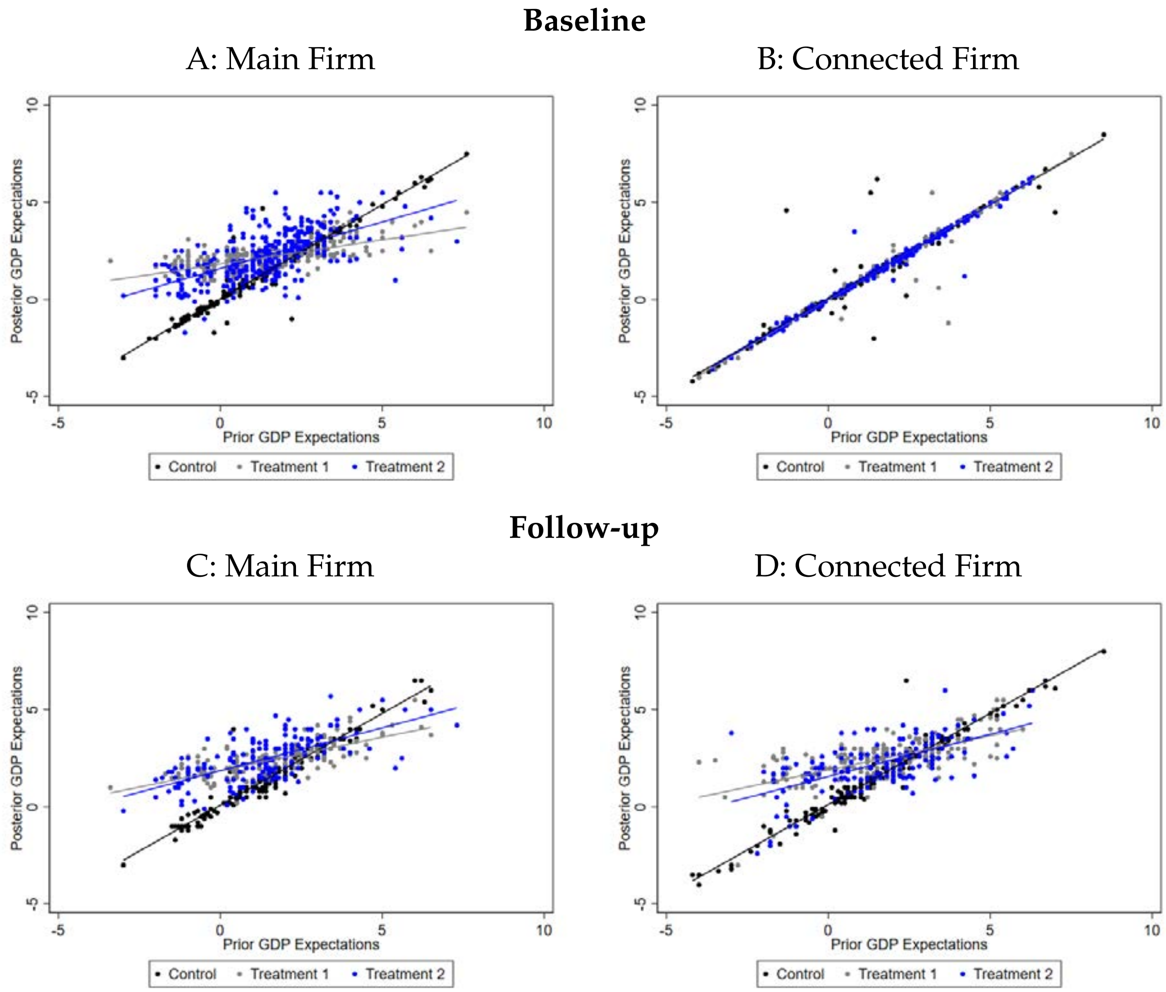
	(1)	(2)	(3)	(4)
$Prior^{mean}$	0.972***	0.964***	0.945***	0.938***
	(0.023)	(0.016)	(0.020)	(0.013)
T_1	1.799***	-0.063	1.787***	1.772***
	(0.068)	(0.044)	(0.070)	(0.112)
T_2	1.567***	-0.040	1.773***	1.433***
	(0.068)	(0.045)	(0.095)	(0.147)
$T_1 \times Prior^{mean}$	-0.723***	0.017	-0.603***	-0.586***
	(0.032)	(0.019)	(0.032)	(0.046)
$T_2 \times Prior^{mean}$	-0.492***	0.006	-0.503***	-0.502***
	(0.032)	(0.018)	(0.046)	(0.061)
Constant	0.025	0.062	0.080	0.120**
	(0.048)	(0.043)	(0.047)	(0.036)
Period Posterior	Baseline	Baseline	Follow-Up	Follow-Up
Type of firm	Main	Connected	Main	Connected
Observations	999	1020	510	505
R-squared	0.739	0.955	0.760	0.743

Note: The table reports results of regression 1, where the outcome variable $Posterior^{mean}$ is the average GDP forecast of firm i after the treatment. $Prior^{mean}$ is the average GDP forecast before the treatment. T_1 is an indicator that is equal to one if firm i received the information treatment about the average GDP forecast and T_2 is an indicator that is equal to one if firm i received the information treatment about the GDP uncertainty. Columns (1) and (2) show results for the baseline survey, and columns (3) and (4) show results for the follow-up survey. Columns (1) and (3) show results for the firms that received the information treatment in the baseline period, and columns (2) and (4) show results for the firms that are connected to the treated firms. Robust standard errors are shown in parentheses.

of smaller magnitude. This is expected given that information about uncertainty in GDP growth is not directly informative about the mean growth. In Panel A of Figure 2, we see a corresponding clockwise rotation of the relationship between posterior and prior, reflecting the reduction in the correlation due to the treatment.

The treatment effect on the connected firm — the spillover effect — in the baseline period (Column 2) from either treatment is insignificantly different from zero.

Figure 2: Correlation between Prior and Posterior for Main and Connected Firms in the Baseline and Follow-up



Note: This figure shows a scatter plot of the expectations about GDP asked before the treatment in the baseline period (prior, x-axis) with either the posterior in the baseline period or the posterior in the follow-up period (y-axis). Panels A and B plot the prior and the posterior in the baseline period. Panel A presents results for treated firms, while Panel B shows the same for connected firms. Panels C and D plot prior expectations in the baseline period against posterior expectations in the follow-up—Panel C for treated firms, Panel D for connected firms. Each dot represents a firm's response; the lines are linear fits by group. Black indicates control firms, gray corresponds to those receiving Treatment 1 (average GDP forecast), and blue to those receiving Treatment 2 (uncertainty information).

Correspondingly, we see no rotation of the distribution in Panel B of Figure 2. As expected, this suggests no information has yet been diffused from the main to the connected firm in the pair. This is because both firms within a pair were surveyed very close in time, while it conceivably takes time for information to be diffused between firms.

Table 2: Treatment Effect on Expected GDP Uncertainty in Baseline and Follow-up

	(1)	(2)	(3)	(4)
$Prior^{Uncertainty}$	0.960***	0.993***	0.978***	0.974***
	(0.019)	(0.010)	(0.019)	(0.018)
T_1	1.395***	0.025	1.310***	2.044***
	(0.198)	(0.084)	(0.302)	(0.328)
T_2	1.145***	-0.015	1.142***	1.139***
	(0.163)	(0.083)	(0.264)	(0.267)
$T_1 \times Prior^{Uncertainty}$	-0.766***	-0.008	-0.717***	-0.761***
	(0.033)	(0.013)	(0.042)	(0.046)
$T_2 \times Prior^{Uncertainty}$	-0.720***	-0.008	-0.689***	-0.610***
	(0.031)	(0.014)	(0.042)	(0.045)
Constant	0.220*	0.067	0.187*	0.276*
	(0.095)	(0.070)	(0.090)	(0.122)
Posterior Period	Baseline	Baseline	Follow-Up	Follow-Up
Firm Type	Main	Connected	Main	Connected
Observations	1012	1022	514	513
R-squared	0.835	0.973	0.809	0.700

Note: The table reports results of regression 1, where the outcome variables $Posterior^{uncertainty}$ is the uncertainty in the GDP forecast of firm i after the treatment, measured as the absolute value on the distance between the most and less likely scenario. $Prior^{uncertainty}$ is the uncertainty forecast before the treatment. T_1 is an indicator that is equal to one if firm i received the information treatment about the average GDP forecast and T_2 is an indicator that is equal to one if firm i received the information treatment about the GDP uncertainty. Columns (1) and (2) show results for the baseline survey, and columns (3) and (4) show results for the follow-up survey. Columns (1) and (3) show results for the firms that received the information treatment in the baseline period, and columns (2) and (4) show results for the firms that are connected to the treated firms. Robust standard errors are shown in parentheses.

Now, turning to the treatment effect in the follow-up period, the direct effect in the follow-up (Column 3) is very similar to the effect in the baseline (Column

1). This suggests that the treatment effect is highly persistent, with the beliefs of the main firm in the follow-up continuing to be highly influenced by the treatment three months earlier. More importantly, the spillover effect in the follow-up (Column 4) is now highly significant. That is, even though the connected firms did not directly receive the information in the baseline, their beliefs three months later had been updated as if they had received the information. Moreover, the magnitudes of spillover effects are remarkably similar to the direct effects (Column 4 vs Column 3). Panels C and D of Figure 2 present the corresponding distributions, showcasing the similarity in their effect.

These findings on the spillover effects are the most interesting and novel part of this paper. This implies that the information about GDP expectations has been diffused from the main firm to the connected firm — i.e., along the supply chain network. In Section 4, we explore the mechanism of this diffusion, specifically whether the firms are engaging in direct communication about GDP expectations, or whether they are inferring them from observable actions.

We present the analogous results for priors and posteriors on the uncertainty of GDP growth, rather than the mean, in Table 2. We find very similar results, both qualitatively and quantitatively. This shows that not only is information about the mean transmitted through the input-output network but also information about uncertainty.

We examine the heterogeneity of the treatment effects with respect to firm characteristics (size, market share, age, and sector) in Table A-4 (a). We detect no systematic variation across these dimensions. This suggests that the information diffuses broadly, rather than being limited to a specific type of firm.

3.2 Treatment Effects on Actions

In this section, we evaluate whether firms changed their decisions/actions due to the information treatment, suggesting that the information content is economically relevant and meaningful. We examine four measures of decisions: price, investment, employment, and wages. These are measured both as *planned* changes reported in the baseline survey (ex-ante plans for the next three months) and as actual *actions* recorded in the follow-up survey (ex-post decisions at the endline).

First, we estimate the reduced-form effect of the treatment on the actions, revealing whether the information caused firms' actions to be less correlated with their initial plans. Second, we use the treatment as an instrument for the firms' GDP expectations to estimate the elasticity of a change in actions with respect to a change in GDP expectations.

The reduced-form regression is the following:

$$Action_i = \alpha + \beta Plan_i + \sum_{n=1}^{2} \gamma_n T_{n,i} + \sum_{n=1}^{2} \theta_n Plan_i \times T_{n,i} + \varepsilon_i, \tag{2}$$

where $Action_i$ is the action the manager of firm i reported in the follow-up period. $Plan_i$ is the firm's plan reported in the baseline period. As in regression 1, $T_{n,i}$ is a dummy that takes a value of one if firm i received the treatment n and zero otherwise. θ_n reflects the correlation of the action and the plan. If the treatment has an effect on the firm's action, then the plan-action correlation will be reduced, corresponding to a negative θ_n. As before, the specification is run separately for main and connected firms to estimate the direct and spillover effects, respectively. We present the results in Table 3.

We find significant treatment effects on prices, employment, and investment (Columns 1 to 6), though not on wages (Columns 7 to 8).[8] Most interestingly, this is the case not only for the direct effects (odd numbered columns) but also for the spillover effects (even numbered columns). Moreover, the magnitudes of the direct and spillover effects for an action are similar, especially for prices and investments. This suggests that the diffusion of information between firms is highly relevant and meaningful for firm operations.

We examine heterogeneity of the treatment effects with respect to firm characteristics in Table A-4 (b). We detect no systematic variation across these dimensions.

Next, we estimate the elasticities of actions with respect to expectations. This is useful to give a clearer sense of the magnitude of the changes in actions due to the

[8]No direct effect on wages is consistent with results in the literature in our setting (Kumar, Gorodnichenko, and Coibion, 2023).

Table 3: Treatment Effect on Wage, Employment, and Investment Plans

	Price		Investment		Employment		Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Plan	1.006***	1.012***	0.975***	0.979***	1.014***	1.017***	0.995***	0.998***
	(0.009)	(0.011)	(0.018)	(0.019)	(0.020)	(0.012)	(0.015)	(0.019)
T_1	1.583***	1.841***	3.448***	3.128***	2.837***	2.291***	-0.024	0.011
	(0.136)	(0.136)	(0.199)	(0.205)	(0.540)	(0.498)	(0.019)	(0.041)
T_2	1.722***	1.815***	2.819***	2.552***	3.388***	2.883***	-0.016	-0.028
	(0.125)	(0.125)	(0.190)	(0.167)	(0.568)	(0.472)	(0.016)	(0.028)
$T_1 \times Plan$	-0.323***	-0.401***	-0.679***	-0.625***	-0.741***	-0.491***	0.005	-0.040
	(0.089)	(0.080)	(0.092)	(0.096)	(0.178)	(0.145)	(0.017)	(0.033)
$T_2 \times Plan$	-0.381***	-0.533***	-0.483***	-0.366***	-1.017***	-0.845***	-0.001	-0.005
	(0.068)	(0.081)	(0.081)	(0.069)	(0.196)	(0.181)	(0.021)	(0.023)
Constant	-0.013	-0.041	-0.002	-0.012	-0.050	0.009	0.012	0.030
	(0.022)	(0.026)	(0.030)	(0.029)	(0.074)	(0.047)	(0.011)	(0.028)
Firm Type	Main	Connected	Main	Connected	Main	Connected	Main	Connected
Observations	512	506	505	512	508	511	505	511
R-squared	0.715	0.629	0.577	0.586	0.324	0.438	0.980	0.981

Note. The table reports results of regression 2, where the outcome variables are actions the firm took in the three months leading up to the follow-up survey. Those actions are the change in prices (columns (1) and (2)), change in investment (columns (3) and (4)), change in employment (columns (5) and (6)), and change in wages (columns (7) and (8)). $Plan$ is the plan that the firm had in the baseline survey for the next three months. T_1 is an indicator that is equal to one if firm i received the information treatment about the average GDP forecast, and T_2 is an indicator that is equal to one if firm i received the information treatment about GDP uncertainty. Columns (1), (3), (5), and (7) show results for the firms that received the information treatment in the baseline period, and columns (2), (4), (6), and (8) show results for the firms that are connected to the treated firms. Robust standard errors are shown in parentheses.

treatment, as it accounts for the changes in expectations attributable to the information treatment. We extend the instrumental variable strategy for direct effects from Coibion, Gorodnichenko, and Weber (2022); Coibion et al. (2023) and Kumar, Gorodnichenko, and Coibion (2023) to spillover effects. For the direct effects, the second stage is given by:

$$Action_i = \alpha + \beta Plan_i + \gamma Posterior_i^{mean} + \theta Posterior_i^{uncertainty} + X_i'\delta + \varepsilon_i, \quad (3)$$

The regression is run on the main firms i. X_i includes priors for mean and uncertainty from the baseline period. The rest of the variables are defined as in specifications 1 and 2. We instrument $Posterior_i^{mean}$ and $Posterior_i^{uncertainty}$ by the treatment interacted with the priors. As we control for the priors, the instrument uses the variation only from the change in expectations induced by the treatment.

Therefore we can interpret the estimates β, γ as causal effects.

To estimate the spillover effects, the specification focuses on connected firms i, while controlling for the corresponding action (and plan) of the main firm, which is instrumented by the treatment interacted with the main firm's plan. The reason for the additional control is the exclusion restriction. The posterior instrument is valid if the only way the treatment affects the connected action is through the connected posteriors. However, it is also possible that the treatment affects the connected firm's action through the main firm's action, without ever having changed the connected posteriors (e.g., the connected firm simply changes its price in response to the main firm changing its price). This would violate the exclusion restriction. We control for the main firm's action to militate against this possibility.

Table 4 reports the results. A 1 percentage point increase in firms' mean GDP growth expectations leads to a statistically insignificant 0.16 percentage point increase in the main firm's prices and a significant 0.42 percentage point increase for connected firms. Employment rises significantly by 0.91 percentage points for the main firm and 0.64 percentage points for connected firms, respectively, relative to their initial plans.[9] We find no significant effect on investment or wages. Regarding expectations of uncertainty, a 1 percentage point increase in uncertainty leads to a 0.34 (0.33) percentage point decrease in the main (connected) firm's prices, a 0.82 (0.52) percentage point decline in investment, and a 0.81 (0.78) percentage point drop in employment, all of which are significant. We find no significant effect on wages.

The opposing effects of the posterior mean and uncertainty on firms' actions align with economic intuition. When firms anticipate economic growth, they increase their prices and employment, as if they expect higher demand for their goods. Conversely, higher uncertainty reduces their prices, investment, and employment decisions, related to the contractionary effect of higher uncertainty (Baker, Bloom, and Terry, 2024). The estimated impact of uncertainty is particularly robust. Moreover, the magnitudes are very similar between main and connected

[9]When we pool main and connected firms, the average effects of mean expectations on prices and employment are significant across all firms; see Table A-6 in the Online Appendix.

Table 4: Causal Effect of Expectations on Actions

	Price		Investment		Employment		Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Posterior^{mean}$	0.163	0.419***	0.008	0.065	0.912**	0.644*	0.024	-0.019
	(0.114)	(0.125)	(0.224)	(0.170)	(0.419)	(0.386)	(0.026)	(0.015)
$Posterior^{uncertainty}$	-0.335***	-0.331***	-0.824***	-0.515***	-0.810***	-0.779***	0.005	0.007
	(0.042)	(0.071)	(0.083)	(0.103)	(0.173)	(0.217)	(0.010)	(0.011)
$Action^{main}$		0.236*		0.317***		0.091		0.348
		(0.139)		(0.083)		(0.083)		(0.323)
Observations	485	453	478	452	479	454	479	452
Firm Type	Main	Connected	Main	Connected	Main	Connected	Main	Connected
F(mean)	110.8	50.7	151.8	48.1	118.9	60.1	109.3	44.0
F(uncertainty)	365.3	187.8	777.3	158.7	402.0	191.0	386.8	191.9
F(action)		45.5		64.6		16.1		0.9

Note. The table reports results of regression 3, where the outcome variables are actions the firm took in the three months leading up to the follow-up survey. Those actions are the change in prices (columns (1) and (2)), change in investment (columns (3) and (4)), change in employment (columns (5) and (6)) and change in wages (columns (7) and (8)). $Posterior^{mean}$ is the GDP forecast of the firm in the follow-up period. $Posterior^{uncertainty}$ is the uncertainty about the GDP forecast of firm i in the follow-up period, measured as the absolute value of the distance between the most and least likely scenario. $Action^{main}$ is the action of the main firm in the follow-up period. Variables not shown but included in the specification: $Plan$ is the plan that the firm had in the baseline survey for the next three months; $Prior^{mean}$ is the GDP forecast of the firm in the baseline period before receiving the treatment, and $Prior^{uncertainty}$ is the uncertainty forecast before the treatment. We instrument the posterior variables with the priors interacted by the treatment dummy. For connected firms, we also instrument the corresponding action of the main firm with the plan interaction by the treatment dummy. Columns (1), (3), (5), and (7) show results for the firms that received the information treatment in the baseline period, and columns (2), (4), (6), and (8) show results for the firms that are connected to the treated firms. The first stage F-statistics are shown at the end of the table. Robust standard errors are shown in parentheses.

firms.

Summarizing, we find that changes in expectations (both first and second moments) significantly affect firms' decisions; this result confirms the findings in Kumar, Gorodnichenko, and Coibion (2023). Most importantly, we present a novel finding: changes in expectation affect the connected firms' actions, and with a magnitude similar to that of the main firms. These findings suggest that information from treated firms is reaching their connected firms, either through direct communication or by inferring expectations from observed changes in actions. We investigate these channels in Section 4. Additionally, in Section 5, we discuss the implications of these findings for the strength of communication.

Regardless of the transmission channel, our findings have important implications for the contagion of expectations within the input-output network. From a policy perspective, central banks could leverage this mechanism to strategically disseminate information throughout the economy. At the same time, it also raises concerns about the potential for pessimistic expectations to propagate, amplifying downturns through network effects.

4 The Role of Communication

In this section, we provide empirical evidence supporting the hypothesis that communication between a firm and its connected firm is an important driver of information diffusion. We especially rule out the alternative explanation that connected firms are solely updating their beliefs because they observe changes in the actions of the main firm. For instance, Table 4 shows that an increase in GDP uncertainty causes the (main) firm that is directly receiving this information to reduce its investment (Column 3). A connected firm, observing this reduction, may interpret it as a signal of increased uncertainty about future GDP growth. We provide three pieces of suggestive evidence indicating that communication is the key channel driving this diffusion.

Decomposing the spillover effects on expectations. We decompose the effect of treatment on the connected firm's posteriors coming from two potential sources: the posteriors and actions of the main firm. An effect operating through the main firm's actions suggests that the connected firm infers its GDP beliefs by observing changes in the main firm's actions. Conversely, any effect via the main firm's posteriors is suggestive of more direct learning of the main firm's beliefs, such as through communication. Specifically, we run the following regression for connected firms i:

$$Posterior_i = \alpha + \underbrace{Posteriors_i^{main\prime}\gamma}_{\text{communication}} + \underbrace{Actions_i^{main\prime}\theta}_{\text{observing actions}} + X_i'\delta + \varepsilon_i, \tag{4}$$

with the dependent variable being the connected firm's mean or uncertainty posterior in the follow-up. The first set of independent variables is the main firm's mean and uncertainty posteriors in the follow-up, instrumented by the treatment interacted with the main firm's priors. The second set is the main firm's actions (prices, investment, employment, wages), instrumented by the treatment interacted with the main firm's corresponding plans. We control for priors of both firms (main and connected) and plans of the main firm. This specification builds on the instrumental variable strategy of Equation (3) and can be interpreted as causal for the same reasons.

Table 5: Decomposing the Spillover Effects on Expectations

	$Posterior^{mean,conn}$		$Posterior^{uncertainty,conn}$	
	(1)	(2)	(3)	(4)
$Posterior^{mean,main}$	0.558***		-0.537***	
	(0.136)		(0.166)	
$Posterior^{uncertainty,main}$	-0.062		0.597***	
	(0.046)		(0.073)	
$Price^{main}$	0.070	0.413**	-0.046	-1.266***
	(0.120)	(0.187)	(0.147)	(0.398)
$Employment^{main}$	-0.025	-0.060	0.040	0.184*
	(0.036)	(0.051)	(0.045)	(0.105)
$Investment^{main}$	0.000	0.068	-0.063	-0.252**
	(0.038)	(0.052)	(0.050)	(0.124)
$Wage^{main}$	-1.603	-4.380	2.136	12.042
	(1.884)	(3.922)	(2.224)	(9.398)
Observations	385	404	385	404
F(mean)	68.3		68.3	
F(uncertainty)	290.5		290.5	
F(price)	24.6	24.4	24.6	24.4
F(employment)	10.7	12.9	10.7	12.9
F(investment)	51.2	50.8	51.2	50.8
F(wage)	0.8	1.0	0.8	1.0

Note: The table reports results of regression (4), where the outcome variables are the mean or uncertainty posteriors in the follow-up of the connected firm in columns (1) and (2), or (3) and (4), respectively. The coefficients are shown for the posteriors and actions in the follow-up of the main firm, which are instrumented by the treatment interacted with the main firm priors and plans, respectively. The first stage F-statistics are shown at the end of the table. In all specifications, we control for priors of the connected firm and plans of the main firm. In columns (1) and (3), we also control for priors of the main firm. Robust standard errors are shown in parentheses.

The results are shown in Table 5. The mean (uncertainty) posterior of the connected firm is shown in Column 1 (2). As can be seen, the coefficients on all main firm actions are insignificant, while they are significant for the main firm posteriors. This suggests that connected firms are *not* forming their macroeconomic beliefs based on the actions of the main firm, but rather from more direct learning about the main firm's beliefs, conceivably through communication. Moreover, this suggests that communication is important for the spillover effect on actions, given that in Table 4 we established that connected firms change their actions in response to their posteriors.[10]

In Columns 3 and 4, we repeat the analysis, excluding the main firm posteriors from the regression. We see that the effect of treatment now loads onto the actions, with some of the coefficients becoming significant. This implies that failing to account for expectations may lead to the mistaken conclusion that firms form their macroeconomic beliefs by observing the actions of others. Accounting for communication — or expectations more generally — of firms in their supply chain, therefore, is an important component for valid inference.

While this provides suggestive evidence, we acknowledge that other unobserved behaviors — such as renegotiation tactics or contractual adjustments — could still serve as alternative sources of signaling. Next, we provide more direct, but self-reported, evidence.

Treated firms report communicating more. In the follow-up wave, we asked each firm how many times it communicated about GDP with the other firm in its pair over the last three months (capturing the time interval since the baseline wave). The distribution of responses is displayed in Figure 3, separately for each treatment group and control.

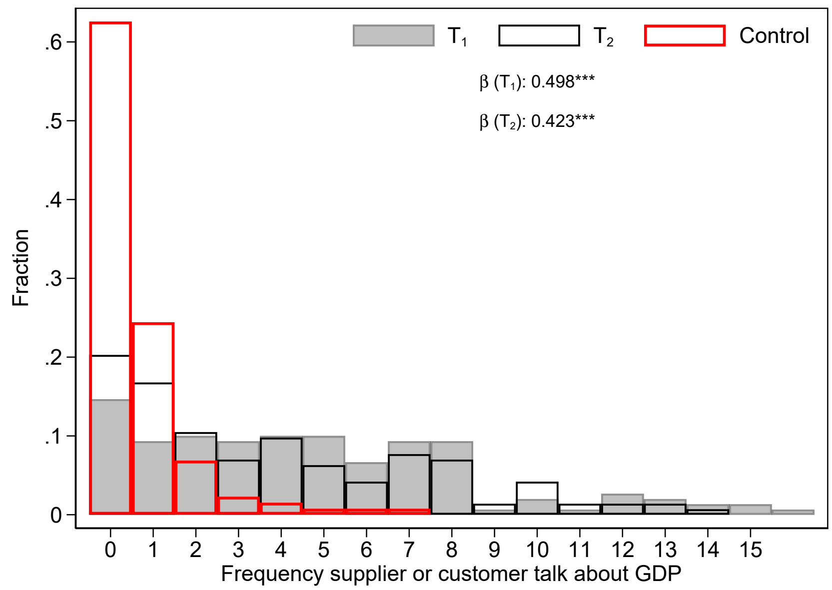
The effect on communication is very strong, with the distribution shifted right under treatment. To give a benchmark, in the control group, 65% of firms report they did not communicate about GDP at all. This is reduced to only 15% (23%)

[10] In Online Appendix Table A-7, we re-run regression (4) but with the actions of the connected firms as the dependent variables. We indeed see that communication appears to be an important driver of the spillover effects on actions.

under mean (uncertainty) treatment, and the reduction is statistically significant. See Table A-8 column (1) for the regression.[11]

The strong effect on the frequency of communication about GDP is consistent with, and suggestive of, communication underlying the effect on beliefs and actions.

Figure 3: Communication about GDP Between Firms



Note: This figure shows the distribution of how many times the main firm reported communicating about GDP with the connected firm, over the three months prior to the follow-up. The distribution is shown separately by treatment group. $\beta(T_n)$ is the treatment effect on communicating at least once.

Effects for upstream and downstream firms are symmetric. Standard production network theory implies that shocks that propagate via actions along supply chains — such as by changes in prices of successive firms — tend to flow asymmetrically upstream vs downstream, more heavily in the former (latter) if the shock is

[11]Table A-8 columns (2)-(4) show the effect on other types of communication: product, industry and economy-wide topics. We find a significantly positive effect on product, and nothing on the other two.

a demand (supply) shock (Carvalho and Tahbaz-Salehi, 2019). Intuitively, the customer cares more about the price of the supplier's product than the supplier cares about the price of the customer's product. Moreover, the strength of the propagation is directly related to the expenditure share between the customer and the supplier firm.

One would likely expect heterogeneity in the spillover effects on expectations along these dimensions if the mechanism is via actions. Table 6 examines this for heterogeneity in the shock flowing upstream vs downstream and the expenditure share between the pair and the number of connections for the main firm. We find no heterogeneity for the effect on expectations with respect to being upstream vs downstream or the number of connections, and little dependence on the expenditure share. Table A-5 in the Online Appendix shows analogous results for the spillover effects on actions, which exhibit some more but still sparse dependence. Together this suggests the mechanism is unlikely to be via actions.

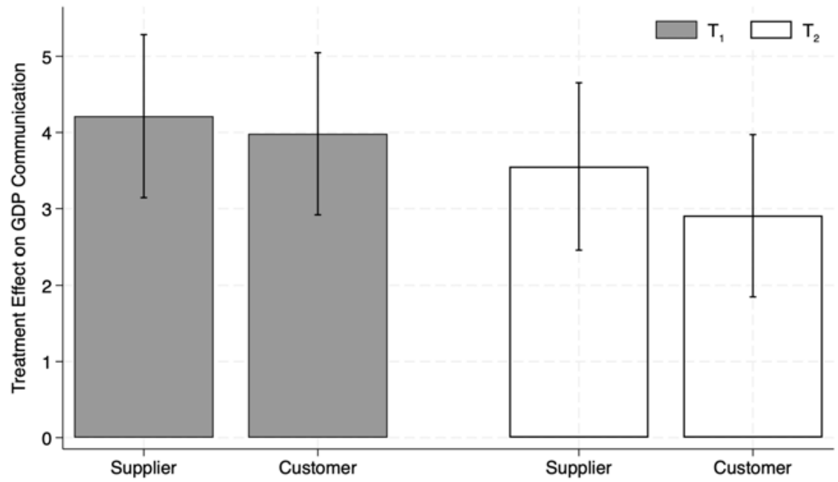
Table 6: Heterogeneous Spillover Effects on Expectations: Network Characteristics

	$Posterior^{mean}$			$Posterior^{uncertainty}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$T_1 \times Prior \times H$	0.100	0.004	0.005	-0.009	0.004	-0.048
	(0.094)	(0.004)	(0.082)	(0.091)	(0.005)	(0.085)
$T_2 \times Prior \times H$	0.114	0.015**	0.016	0.008	0.004	0.006
	(0.125)	(0.007)	(0.123)	(0.090)	(0.004)	(0.089)
Heterogeneity, H	Upstream	Exp. Share	N connections	Upstream	Exp. Share	N connections
N	505	354	381	513	360	389

Note. The specifications extend the regression of equation (1) to include an interaction of each term with variable H, for the sample of connected firms. Each column uses a different characteristic of the main firm for H, as labeled (a dummy equal to one if the customer, share of sales to or expenditure on the connected firm, and number of customers or suppliers — if they are a supplier or customer, respectively, in the latter two). Only the triple interaction terms are displayed, which identifies the effect of H on the correlation of the posterior with the prior. $Prior$ corresponds to mean (connected) in columns 1-3 (4-6). Standard errors are displayed in parentheses.

Given this symmetry, for communication to instead be the mechanism it must be that communication between firms is symmetric upstream vs downstream. Figure 4 shows that this is indeed the case. For either treatment, the number of times the main firm reports communicating about GDP (relative to control) is not statistically different whether it is a supplier or a customer.[12] Thus, communication as the underlying mechanism is consistent with the results.

Figure 4: Communication about GDP: Upstream vs Downstream



Note: This figure shows the treatment effect on the number of times the main firm reported communicating with the connected firm about GDP, during the three months prior to the follow-up. This is shown separately for each treatment, T_n, and separately for whether the main firm is the supplier or the customer in the pair. 95% confidence intervals are displayed.

This is an interesting result in itself because we may have expected communication to be asymmetric along the supply chain due to strategic considerations. For instance, a customer firm may not want to disclose positive information about the macroeconomy to the supplier in case this prompts the supplier to increase its prices. The supplier, on the other hand, may well want to disclose this information, as it may prompt the customer to buy more from it.

Figure A-2 provides corroborating evidence that such strategic behavior is limited in our setting. Only 118 firms reported "gaining a competitive advantage" as a reason for sharing information about GDP, while 446 reported "fostering innovation and collaboration." When it comes to information about GDP at least, our results suggest that firms are more collaborative than deceptive.

[12]We find similar effects for the connected firms (Figure A-1).

5 Macroeconomic Implications

To understand the role of communication for firms' expectations formation and pricing decisions, we introduce communication along a production network in a New Keynesian pricing problem. We focus on pricing decisions because they are the key link between supplier and customer firms in a supply chain network. In what follows we show that in the context of shocks to output growth expectations, communication has implications for the propagation of shocks, price dispersion, and aggregate inflation dynamics.

5.1 Setup

We consider the sector-level Phillips curve derived in Rubbo (2023) and assume each of the N sectors is represented by a firm. The price vector $\boldsymbol{p}_t$ is given by[13]

$$\boldsymbol{p}_t = \Delta \left(\boldsymbol{\kappa} y_t + \beta \Omega \widetilde{\mathbb{E}}_t \left[\boldsymbol{p}_{t+1} \right] + \Omega \boldsymbol{p}_{t-1} \right), \tag{5}$$

where y_t is a measure of slack in the economy that we assume to be output growth in deviation from the steady state; $\widetilde{\mathbb{E}}_t$ is a *generic* expectations operator, possibly different from the full-information rational expectations one; β denotes the discount factor; Ω is an invertible matrix whose elements are convoluted expressions of the intensity of input-output linkages ($IO \equiv [\iota_{ij}]$ matrix) among firms as well as their labor shares ($\boldsymbol{\alpha} \equiv [\alpha_i]$ vector), price flexibility ($\Phi \equiv [\phi_i]$ diagonal matrix), and consumption shares ($\boldsymbol{\psi} \equiv [\psi_i]$ vector); $\boldsymbol{\kappa}$ is the vector of Phillips curve slopes; and $\Delta = (I + \beta\Omega)^{-1}$.[14]

Output growth is assumed to be exogenously given and is driven by an iid

[13]The vector of firm-level inflation rates is described by $\boldsymbol{\pi}_t = \boldsymbol{p}_t - \boldsymbol{p}_{t-1} = \beta\Omega\widetilde{\mathbb{E}}_t\left[\boldsymbol{\pi}_{t+1}\right] + \boldsymbol{\kappa} y_t - (I - \Omega)\boldsymbol{p}_{t-1}$. We note that our setting abstracts from productivity shocks, implying that all of our results go through even if the slack in the economy is measured by the output gap—which equals output in the absence of productivity shocks—as in Rubbo (2023).

[14]As proved by Rubbo (2023), Ω is invertible as long as no firm has fully flexible prices. We describe the structure of the matrices and vectors in equation (5) in Online Appendix B.1 in more detail.

shock, ε^*_{t+1}, with mean zero and variance σ^2_ε, and a deterministic sequence μ^*_t:

$$y_{t+1} = \mu^*_t + \varepsilon^*_{t+1}. \tag{6}$$

The long-run behavior of μ^*_t is assumed to converge to that of an iid normal stochastic process with mean 0 and standard deviation σ_{μ^*}, and that is independent of the process for ε^*_t. Similar to Ilut and Schneider (2014), we assume that firms cannot distinguish the deterministic sequence from the iid shocks even if they observe an infinitely large amount of data. As a result, equation (6) describes a large family of possible processes that can have rather different implications in the short run, for example, because they differ in the conditional mean μ^*_t. This is consequential because, by iterating equation (5) forward, a firm's optimal pricing decision depends on its expected future output growth, that is, its perceived μ^*_t.

5.2 Output Growth Expectations

To solve the model we have to discipline firms' expectations about future growth. In doing so, we consider three components that we describe in detail below.

Uncertainty. We assume that firms face Knightian uncertainty and are averse to ambiguity arising from not being able to distinguish the deterministic component from the iid component of growth. Firms then base their actions on the most pessimistic possible outcome. To discipline the firms' belief set for output growth, we follow a strategy similar to that in Ilut and Schneider (2014). Specifically, firm j's *perceived* law of motion about output growth in deviation from the steady state is given by

$$y_{t+1} = \mu_{jt} + \varepsilon_{j,t+1}, \qquad \mu_{jt} \in [-a_{jt}, -a_{jt} + 2|a_{jt} + \bar{a}|] \tag{7}$$

where firm j perceives the deterministic component of growth to range between $-a_{jt}$ and $-a_{jt} + 2|a_{jt} + \bar{a}|$ with a_{jt} being a mean 0 iid shock around the steady-state ambiguity level $\bar{a} > 0$, and the realized a_{jt} is assumed small enough so that

$\bar{a} + a_{jt} > 0$.[15] A wider range for μ_{jt}, that is, a larger $|a_{jt} + \bar{a}|$ or equivalently higher a_{jt}, also implies a lower worst case scenario for output growth. Since firms base their actions on the most pessimistic possible outcome, their prior expectations about future output growth are given by

$$\widetilde{\mathbb{E}}_{jt}^{prior} y_{t+1} = \min_{\mu_{jt} \in [-a_{jt}, -a_{jt}+2|a_{jt}+\bar{a}|]} \mu_{jt} = -a_{jt}. \tag{8}$$

Information treatment. As in the experiment, treated firm j receives information about professional forecasters' range around their output growth forecast, which firm j interprets to equal $2|a_t^* + \bar{a}|$ so that it is centered at $\bar{a}$ just like μ_{jt}.[16] Upon receiving this information, the firm updates its expectations about future output growth to

$$\widetilde{\mathbb{E}}_{jt}^{post} y_{t+1} = -a_{jt}(1 - g_j) + g_j s_{jt}, \tag{9}$$

where $s_{jt} = -a_t^*$ if firm j is treated and $s_{jt} = 0$ otherwise; $g_j \in [0, 1]$ denotes the gain from the information treatment.[17] We hereafter interchangeably refer to s_{jt} as a signal or treatment.

Communication. Consistent with our empirical evidence, we assume firms communicate their expectations about future output growth with each other according to an exogenous communication matrix $\mathcal{C}$, described in Definition 1, that firms take as given.[18]

[15] Ilut and Schneider (2014) lay out the equation that is analogous to our equation (7) before expressing variables in deviation from their steady state. The corresponding range around the deterministic component in that case would be $\left[-a_{jt} - \bar{a}, -a_{jt} - \bar{a} + 2|a_{jt} + \bar{a}|\right]$. Moreover, output growth and its deterministic component are perceived to converge to $-\bar{a}$; hence subtracting by $-\bar{a}$ in the range above yields the range for μ_{jt} in equation (7). Therefore, a_{jt} describes ambiguity around a forecast of output growth in deviation from the steady state that equals $\bar{a}$, or ambiguity around a forecast of no output growth.

[16] Our analysis goes through similarly in the case of a treatment about μ_t^*, corresponding to treatment 1 in our empirical analysis.

[17] The treated firm updates the lower bound of the deterministic component range to $-(1 - g_j)a_{jt} - g_j a_t^*$.

[18] This rules out firms strategically choosing to communicate parts of information with other firms (i.e., endogenous $\mathcal{C}$). This is reasonable in our setting as we do not find evidence of any strategic behavior (see Section 4).

DEFINITION 1. *The communication network is described by matrix $\mathcal{C} = [c_{ij}]$, where $c_{ij} \in [0, 1]$ quantifies the intensity with which firm j communicates its expectations about future output growth to firm i, so that $\sum_{j=1}^{N} c_{ij} = 1$. No communication corresponds to $\mathcal{C} = I$, and we define even communication as $\mathcal{C} = \mathbf{1}_{N\times N}/N$.*

Even communication is the case where all firms communicate equally with one-another, which is motivated by the empirical evidence of symmetric communication (Figure 4).[19] The *final* expectations of any firm i about output growth are given by

$$\widetilde{\mathbb{E}}_{it} y_{t+1} = \underbrace{\left(1 - \sum_{j\neq i}^{N} c_{ij}\right)}_{=c_{ii}} \widetilde{\mathbb{E}}_{it}^{post} y_{t+1} + \sum_{j\neq i}^{N} c_{ij} \widetilde{\mathbb{E}}_{jt}^{post} y_{t+1}, \tag{10}$$

where $\sum_{j\neq i}^{N} c_{ij} = (1 - c_{ii})$ is the total exposure to information from communication. The vector of all firms' expectations about future growth can be written as

$$\widetilde{\mathbb{E}}_t \boldsymbol{y}_{t+1} = \mathcal{C}\left[-(I - G)\boldsymbol{a}_t + G\boldsymbol{s}_t\right] \tag{11}$$

where $\boldsymbol{y}_t = \mathbf{1} y_t$, $\boldsymbol{a}_t$ is the vector of firm ambiguity, G is a diagonal matrix whose diagonal equals firm gain from information treatment, and $\boldsymbol{s}_t$ is the vector of signals.[20]

[19] Our empirical evidence highlights symmetry in communication between any supplier-customer pairs of firms, which we extend to apply to the rest of the network to which our pair is connected. It is plausible that the intensity of communication between the supplier or customer firms and the rest of the network is asymmetric. However, since we do not observe the intensities with which our supplier and customer firms communicate with the rest of their network, even communication is a useful and informative benchmark that also enables us to derive some analytical results.

[20] We note that if there is perfect information about μ_t^*, and, as a result, there is no ambiguity about the deterministic component of growth, that is, $a_{it} = 0$ for any firm i, then the model recovers the one in Rubbo (2023), which abstracts from imperfect information, ambiguity aversion, and communication networks. Firms being fully informed about μ_t^* and rational implies that firms' communication about their expectations of output growth is irrelevant since all firms share the same expectations, $\widetilde{\mathbb{E}}_{it} y_{t+1} = \mu_t^*$ for any i.

5.3 Solution and Implications

We now turn to the solution of the model and the implications of communication for firms' prices, the aggregate price level, and inflation.

Price vector. Proposition 1 provides the equilibrium price vector and shows that an information treatment about higher uncertainty (lower s_{jt}) leads to lower prices, as documented by our empirical results in Table 4.

PROPOSITION 1. *The equilibrium price vector is described by*

$$\boldsymbol{p}_t = \beta M \mathcal{C} \left(G \boldsymbol{s}_t - (I - G) \boldsymbol{a}_t \right) + M_y \boldsymbol{y}_t + M_p \boldsymbol{p}_{t-1},$$

where $M = M_p \times M_y$ and all its elements are positive.

The impact of a treatment to firm j on the price of firm i can be decomposed into

$$\frac{\partial p_{it}}{\partial s_{jt}} = \underbrace{\beta M_{ij} c_{jj} g_j}_{\text{treated firm action channel}} + \underbrace{\beta \sum_{k \neq j} M_{ik} c_{kj} g_j}_{\text{treated firm communication channel}} \geq 0. \tag{12}$$

The first component describes the effect of treatments to the extent that the actions of the treated firm affect firm i, as captured by M_{ij}. The second component describes the communication effect that results from the treated firm sharing information with its production network (including i) and those firms reacting to the new information. Absent communication ($\mathcal{C} = I$), firm i's price will only respond to the treatment s_{jt} via the actions of the treated firm j (the first component). The communication channel (the second component) becomes more important for the effect on firm i's price as communication increases.[21]

Corollary 1 formalizes our symmetry result: under even communication ($\mathcal{C} = \mathbf{1}_{N \times N}/N$), the reaction of all firms' expectations and prices is independent of where the treatment originates. Hence, even communication implies a symmetric upstream vs downstream propagation of shocks to output growth expectations.

[21]We note that if all firms receive the same signal about future growth and update their expectations similarly ($G = gI$), communication has no effect on output growth expectations.

COROLLARY 1. *Suppose all treated firms place the same weight on the treatment ($g_j = g$, $\forall j$). The firm where the treatment originates is irrelevant for the response of output growth expectations and prices under even communication, that is,* $\frac{\partial \widetilde{\mathbb{E}}_{it} y_{t+1}}{\partial s_{jt}} = \frac{\partial \widetilde{\mathbb{E}}_{it} y_{t+1}}{\partial s_{kt}}$ *and* $\frac{\partial p_{it}}{\partial s_{jt}} = \frac{\partial p_{it}}{\partial s_{kt}}$, *$\forall i$ and $\forall j \neq k$.*

In contrast to Corollary 1 that characterizes the response of a given firm's price when varying the treated firm, Corollary 2 characterizes the dispersion in price responses across firms for a given treated firm. Specifically, Corollary 2 proves that for a given information treatment s_{jt}, the initial price response varies across firms when communication is absent. While, in the presence of even communication, there is price dispersion only to the extent that firms' Phillips curve slopes are heterogeneous.

COROLLARY 2. *Suppose all treated firms place the same weight on the treatment ($g_j = g$, $\forall j$). Following a treatment to firm j, there will always be dispersion in the initial firm price responses absent communication; under even communication, there will be dispersion in the initial firm price responses only to the extent that the Phillips curve slopes, $\boldsymbol{\kappa}$, are heterogeneous.*

Aggregate price level and inflation. A one-time treatment about future output growth uncertainty causes a permanent shift in the price vector and in the aggregate price level, defined as $P_t = \boldsymbol{\psi}' \boldsymbol{p}_t$, where $\boldsymbol{\psi}$ is the vector of consumption shares. It is straightforward that the symmetry result in Corollary 1 carries over similarly for the aggregate price. Firms adjust their prices until they converge to the new long-run aggregate price level. Proposition 2 shows that the response of the long-run aggregate price to an information treatment s_{jt} depends on the interaction between firms' Domar weights, their price flexibility, their Phillips curve slopes, their intensity of communication with the treated firm j, and firm j's gain from the treatment.

PROPOSITION 2. *Following a one-time unit signal about future output growth received by firm j, the aggregate price level converges to*

$$\lim_{h\to\infty} P_{t+h} = \lim_{t\to\infty} \boldsymbol{\psi}' \boldsymbol{p}_{t+h} = \frac{\beta \boldsymbol{\lambda}(I-\Phi)\Phi^{-1} diag(\boldsymbol{\kappa}) \mathcal{C}_{:,j} g_j}{\sum_i \boldsymbol{\lambda}_i},$$

where $\boldsymbol{\lambda} = \boldsymbol{\psi}'(I - IO)^{-1}$ is the vector of Domar weights that measure firm size.

Corollary 3 formalizes the condition for which communication amplifies the response of the long-run aggregate price level to an information treatment received by firm j.

COROLLARY 3. *Relative to no communication, even communication amplifies the response of the long-run aggregate price to a treatment received by firm j if the following inequality is satisfied:*

$$\frac{\boldsymbol{\lambda}_j \boldsymbol{\kappa}_j (1 - \phi_j)}{\phi_j} < \sum_{i \neq j}^{N} \frac{\boldsymbol{\lambda}_i \boldsymbol{\kappa}_i (1 - \phi_i)}{\phi_i (N - 1)}, \tag{13}$$

where $\boldsymbol{\lambda} = \boldsymbol{\psi}'(I - IO)^{-1}$ is the vector of Domar weights that measure firm size. A more positive difference between the right-hand side and left-hand side in (13) implies a larger amplifying effect of communication on the long-run aggregate price compared to no communication.

When multiplied by g_j, the left-hand side of the inequality in equation (13) coincides with the response of the long-run aggregate price to a treatment provided to firm j, in the absence of communication. An insight of Corollary 3 is then that communication has stronger propagative effects—relative to no communication—on the long-run price level when treating a firm that, absent communication, triggers a weaker effect on the long-run aggregate price.

In the special case when firms have similar price flexibility and Phillips curve slopes, communication has stronger propagative effects on the long-run aggregate price the smaller the treated firm's Domar weight is relative to the rest of the firms in the network. If firms also have the same consumption shares ($\boldsymbol{\psi} = \mathbf{1}/N$), a smaller Domar weight corresponds to being more downstream, implying higher propagative effects of communication when the treatment originates from the customer firm (downstream) as opposed to the supplier firm (upstream) in any supplier-customer pair.[22] Intuitively, a customer firm's product price is less relevant for its supplier, than the supplier's price is for the customer. Thus, absent communication, shock propagation is weaker when originating downstream.

[22] The upstreamness is measured by $\mathbf{1}'((I - IO)^{-1} - I)$; see Carvalho and Tahbaz-Salehi (2019).

Aggregate inflation is equal to $\bar{\pi}_t = \boldsymbol{\psi}'(\boldsymbol{p}_t - \boldsymbol{p}_{t-1})$. Given that $\boldsymbol{p}_{t-1}$ is predetermined, the symmetry result of Corollary 1 for $\boldsymbol{p}_t$ carries over with the treatment origin being irrelevant for aggregate inflation under even communication. Using Proposition 1 to solve for aggregate inflation,

$$\bar{\pi}_t = \boldsymbol{\psi}' \left[\beta M \mathcal{C} \left(G\boldsymbol{s}_t - (I-G)\boldsymbol{a}_t\right) + M_y \boldsymbol{y}_t + (M_p - I)\boldsymbol{p}_{t-1}\right]. \tag{14}$$

Noting that $\sum_{j=1}^{N}(M_p - I)_{ij} = 0 \; \forall i$, then communication lowers the persistence of the aggregate inflation response to the extent that it homogenizes the initial price responses across firms. Intuitively, the treatment will affect future inflation to the extent that current prices have not reached the new long-term aggregate price level. Homogeneity in the initial price responses implies immediate adjustment of all prices to the new aggregate price level.[23]

5.4 Quantitative Analysis

We now explore the role of communication quantitatively. To be close to the empirical setup, we consider a three-firm model, where one firm is the customer firm (firm 3), one the supplier firm (firm 2), and the other one captures the rest of the network (firm 1). The customer firm purchases its inputs from firms 1 and 2, while the supplier purchases its inputs only from firm 1.[24] We simulate the price vector response to a one-time unit information treatment for different values of the supplier's and customer's input shares in the case of no communication and even communication.[25] We calibrate the model to match key characteristics of firms in

[23]From Proposition 1 and $\sum_j (M_p)_{ij} = 1 \; \forall i$, it follows that if the initial price response is homogeneous, $\boldsymbol{p}_t \propto \mathbf{1}$, then $\boldsymbol{p}_{t+h} = \boldsymbol{p}_t$ and $P_{t+h} = P_t$, $\forall h > 0$. The dynamics in this case mirrors that of the representative firm model, with standard Phillips curve $\pi_t = \beta \widetilde{\mathbb{E}}_t \pi_{t+1} + \boldsymbol{\kappa} y_t$. A one-time treatment about future output growth uncertainty in period t will lead to a one-time change in inflation in period t, after which inflation reverts to its steady state.

[24]The assumed structure of the network implies the following input-output matrix and labor share vector: $IO = \begin{bmatrix} 0 & 0 & 0 \\ \iota_{21} & 0 & 0 \\ \iota_{31} & \iota_{32} & 0 \end{bmatrix}$ and $\boldsymbol{\alpha} = \begin{bmatrix} 1 & \alpha_2 & \alpha_3 \end{bmatrix}'$, so that $IO + \boldsymbol{\alpha} = \mathbf{1}$.

[25]In Online Appendix B.3, we consider another communication strategy with $\mathcal{C} = \Omega$, so that the intensity of communication equals the sensitivity of the firms' price changes to the vector of future

our sample, such as price flexibility and labor cost share, while setting other parameters to standard values. We describe the calibration strategy and details of the simulation exercise in Online Appendix B.1 and focus next on our three results from the simulation exercise.

Result 1: Communication generates symmetry in upstream vs downstream transmission of a treatment. Figure 5 plots the distribution of the initial response of firm prices to an information treatment about higher growth uncertainty provided to the supplier (left panel) and to the customer (right panel). The red distributions in Figure 5 show that when firms communicate, whether the treatment was provided to the supplier or the customer firm does not matter for its impact on prices, as stated in Corollary 1. By contrast, absent communication, the origin of the treatment matters for the price responses, as visualized by the vastly different blue distributions in the left and right panels. This result is consistent with our empirical evidence in Table 6 of the symmetric spillover effects of treatments on connected firms.

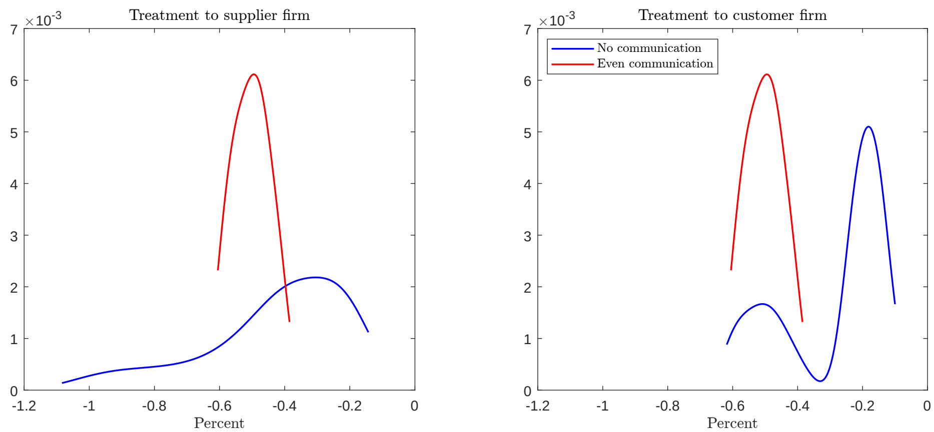
Result 2: Communication reduces the dispersion of price responses to a treatment. Figure 5 further shows that communication heavily reduces the dispersion of price changes on impact following a treatment to the supplier or customer: as Corollary 2 highlights, any remaining price dispersion when firms communicate is explained by their heterogeneous Phillips curve slopes.[26] The low price dispersion under communication is consistent with our empirical results: most treated firms report communicating (Figure 3) and the average treatment effect on prices is almost identical for the main and connected firms (Table 3, Columns 1 and 2).

A more direct empirical validation would be contrasting the treatment effects on prices for firms that do and do not communicate, expecting greater divergence in the latter. Although exogenous variation in communication would be needed for definitive evidence — which we do not have — we nonetheless show the re-

expected price changes.

[26]Figure A-3 in the Online Appendix shows that the reduction in price dispersion holds true across firms within each three-firm network.

Figure 5: Distribution of the Impact on Prices after Treatments of Higher Uncertainty



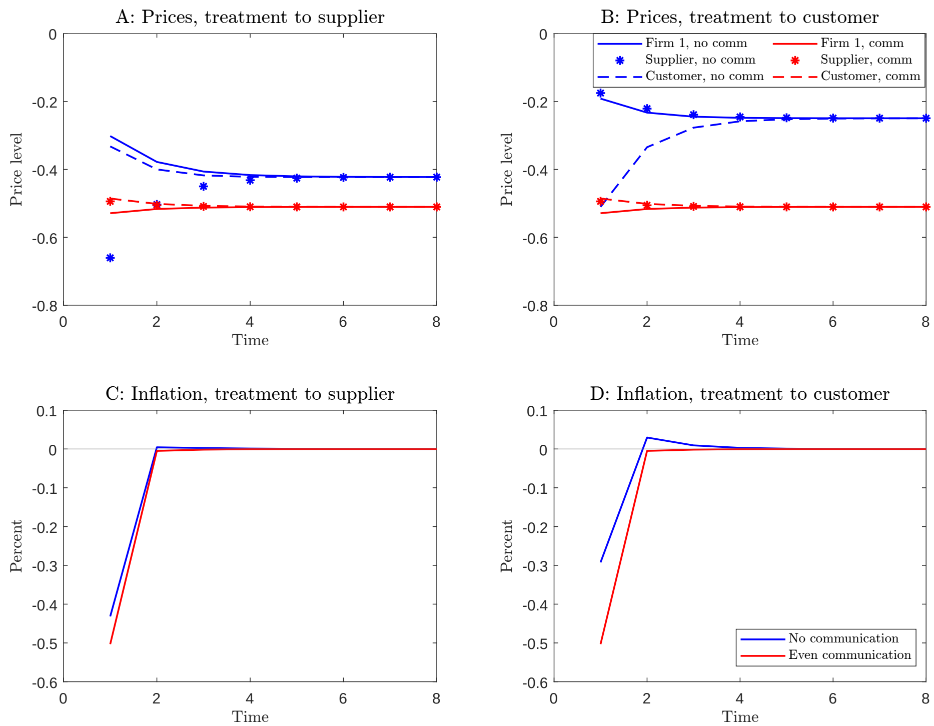
Note: Distribution of initial price responses across all three firms when the treated firm is the supplier (left panel) and when the treated firm is the customer (right panel). In red: even communication; in blue: no communication.

sults of this exercise in Table A-10 in the Online Appendix. In both the data and the simulations, we compute the connected firm's price change associated with a 1 percentage point exogenous rise in the treated firm's price. We find that when there is communication, the estimated price relationship between the treated and connected firm approaches unity both empirically and in the model, regardless of whether the treatment was provided to a customer or a supplier firm.[27] Absent communication, the point estimate of the price relationship is always less then unity, but higher when the treatment is provided to the supplier compared to when the treatment is given to the customer—both in the survey data and in the model simulations.

Result 3: Communication leads to a stronger and shorter-lived response of inflation to future output growth uncertainty. Panels A and B in Figure 6 plot the evolution of firm prices over time, averaged across simulations, when the supplier

[27]This result can explain why other works, such as Carvalho et al. (2021), find a similar propagation of shocks for downstream and upstream firms.

Figure 6: Evolution of Prices and Aggregate Inflation after Treatments of Higher Uncertainty



Note: Panels A and B plot the evolution of price levels, averaged across simulations, when a treatment of higher uncertainty about future output growth is provided to the supplier and customer. Panels C and D plot the evolution of aggregate inflation, implied by the price dynamics in panels A and B. In red: even communication; in blue: no communication.

is treated (left panel) and when the customer is treated (right panel). Communication amplifies the average response of the long-run aggregate price level, with larger amplification compared to the no communication case when the treated firm is the customer compared to the supplier. This is consistent with Corollary 3, noting that the customer firm is the most downstream firm in the network (small Domar weight).

Panels C and D show that communication amplifies the average impact of future output growth uncertainty on inflation, consistent with communication amplifying the initial price response of most firms, relative to no communication, as shown in Figure 5.[28] However, since there is little price dispersion in the presence of communication (from Result 2 above), this effect is very short-lived. The result of Corollary 1 that the firm where the treatment originates is irrelevant for the response of prices is also evident for inflation dynamics. Absent communication, inflation dynamics depend on whether the treated firm is the supplier or the customer.

Other macroeconomic implications. We end this section with a broader discussion of two additional macroeconomic implications of communication that we leave to be explored in more depth in future research. First, our empirical and model analyses show that shocks to the output growth expectations of firms can influence other firms in the network not only through the production network but also through communication. Consequently, accounting for firms' expectations is even more important in the context of production networks complemented by communication networks when estimating structural parameters, such as the slope of the Phillips curve. Table A-9 in the Online Appendix shows that in our setting, where communication appears to be abundant, not accounting for the connected firm's expectations would overestimate by three times the effect on their prices from a marginal cost shock (main firm's price instrumented by our treatment, for the set of connected firms that are customers).[29]

Second, our result that inter-firm communication is a key channel through which firms' beliefs propagate can help policymakers design alternative policy communication strategies. For instance in anchoring firms' expectations, policy communication efforts can be focused on firms that are central to the production network and that communicate with many other firms. This insight complements findings in the literature such as how monetary authorities should choose optimal weights for their objective price index (La'O and Tahbaz-Salehi, 2022; Rubbo,

[28]The propagative effects of communication have also been emphasized in Angeletos and La'O (2013) in the context of sentiment shocks.

[29]That is, comparing the coefficient on $Action^{main}$ in column 2 (not controlling for expectations) vs column 1 (controlling for expectations). The other columns show the affect on other actions. All regressions are for connected firms that are customers.

2023), and how fiscal policy targeting specific sectors can support traditional monetary policy (Cox et al., 2024).

6 Conclusion

Using a randomized controlled trial applied to a sample of firm-firm pairs, we examine the role that input-output linkages play for the expectations formation process of firms. Exploiting exogenous variation from an information treatment—which provided either GDP growth or uncertainty forecasts—we show that firms update their expectations, and these revisions lead to changes in economic decisions, including pricing, investment, and employment.

Notably, the effect of information treatments on expectations and key decisions is observed not only among the directly treated firms but also among firms connected to them, suggesting that information propagates beyond those who receive it firsthand. To better understand the transmission mechanism, we decompose the treatment effect on connected firms' expectations into two channels: one driven by observed actions and the other by the posterior expectations of treated firms, likely reflecting direct communication. Our results provide suggestive evidence that the latter is a key driver of the spillover in expectations. Supporting this interpretation, we find that communication between firm pairs is significantly higher when one firm in the pair is treated, and that the spillover effects on expectations are symmetric upstream vs downstream, which would be difficult to explain absent communication.

To better assess communication as a transmission mechanism of shocks, we integrate a communication network along the production network in a New Keynesian pricing problem. We explore the results of the model quantitatively when a subset of firms receive information about higher uncertainty about future output growth. We find that communication leads to symmetric transmission of treatments upstream vs downstream and it homogenizes the response of prices to treatments. We further find that communication amplifies the response of the aggregate price level in the long-run and that it leads to a stronger but shorter-lived response of aggregate inflation to future output growth uncertainty. Finally, our results highlight the importance of accounting for firms' expectations when estimating structural parameters—such as the Phillips curve slope—and can provide insights for designing alternative policy communication strategies.

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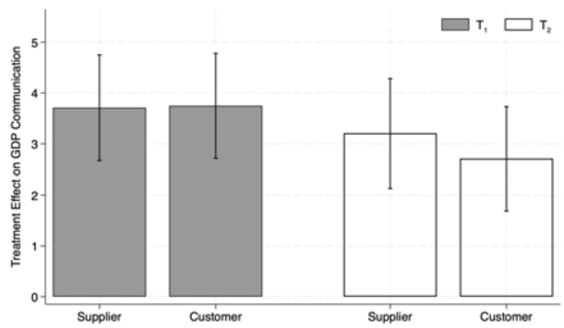
Supplemental Appendix

A Additional Figures and Tables

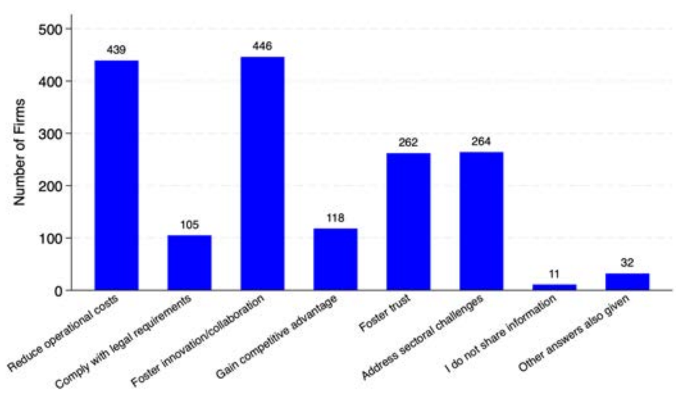
A.1 Figures

Figure A-1: Communication about GDP: Upstream vs Downstream (Connected Firms)



Note: This figure shows the treatment effect on the number of times the connected firm reported communicating with the main firm about GDP, during the three months prior to the follow-up. This is shown separately for each treatment, T_n, and separately whether the main firm is the supplier or customer in the pair. 95% confidence intervals are displayed.

Figure A-2: Reasons for Sharing Information about GDP



Note: The number of firms (main and connected) listing the labeled response as a reason for sharing information about GDP.

A.2 Tables

Table A-1: Firm Counts and Percentages by Sector and Size Category

	5 or less Workers		6–19 Workers		20–49 Workers		50+ Workers		Totals	
	Number	%	Number	%	Number	%	Number	%	Number	%
Panel A: Stats NZ Records										
Manufacturing	5286	48	3663	33	1239	11	771	7	10959	100
Wholesale Trade	4107	54	2328	31	705	9	396	5	7536	100
Retail Trade	7317	58	3945	31	735	6	618	5	12615	100
Totals	16710	54	9936	32	2679	9	1785	6	31110	100
Panel B: Firms Approached										
Manufacturing	2610	46	1934	34	729	13	347	6	5620	51
Wholesale Trade	2451	51	1622	34	433	9	307	6	4813	64
Retail Trade	3122	54	1996	35	295	5	364	6	5777	46
Totals	8183	50	5552	34	1457	9	1018	6	16210	52
Panel C: Main Wave Firms Sample										
Manufacturing	70	3	444	23	362	50	251	72	1127	20
Wholesale Trade	45	2	212	13	157	36	99	32	513	11
Retail Trade	95	3	195	10	175	59	43	12	508	9
Totals	210	3	851	15	694	48	393	39	2148	13
Panel D: Follow-up Firms Sample										
Manufacturing	31	44	230	52	198	55	130	52	589	52
Wholesale Trade	18	40	111	52	72	46	47	47	248	48
Retail Trade	33	35	109	56	73	42	26	60	241	47
Totals	82	39	450	53	343	49	203	52	1078	50

Note: This table summarizes the number of firms and their percentage shares by sector and firm size category across different survey stages. Panels A and B are population and approached samples, respectively, while Panels C and D represent the main and follow-up survey samples. Percentages in A and B are shares of the population and sum to 100 within a row (excluding the last column). Percentages in C and D are response rates: they are the share of observations relative to the same cell in the panel above.

Table A-2: Treatment Prediction of Firms' Characteristics

	(1)	(2)	(3)	(4)	(5)
	Employment (log)	Industry	N of Relationships	Firm Age	GDP Prior
Treatment 1	-0.017	0.121	0.374	-2.891**	0.113
	(0.053)	(0.130)	(0.450)	(1.331)	(0.097)
Treatment 2	-0.077	-0.013	0.226	-6.752***	0.031
	(0.051)	(0.128)	(0.439)	(1.279)	(0.097)
Observations	2,010	2,010	1,799	1,722	2,010
R-squared	0.001	0.001	0.000	0.016	0.001

Note. The table reports results of regression where the dependent variable is either Employment in logs (Column 1), whether the firm is in the manufacturing or trade industry (Column 2), number of firms' customers and supplier (Column 3), firms' age (Column 4), or the prior GDP expectation (Column 5). The independent variables take a value of one if the firm received treatment 1 or 2 and zero otherwise, respectively. Robust standard errors in parenthesis. Constant is not included in the table.

Table A-3: Predictability of Participation in the Follow-up Wave

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment 1	0.036	0.036	0.039	0.038	0.023	0.034
	(0.027)	(0.027)	(0.027)	(0.027)	(0.029)	(0.032)
Treatment 2	-0.023	-0.022	-0.021	-0.023	-0.023	-0.002
	(0.027)	(0.027)	(0.027)	(0.027)	(0.029)	(0.032)
Employment (log)		0.019	0.016	0.014	0.004	0.004
		(0.011)	(0.012)	(0.012)	(0.013)	(0.015)
Industry: Trade			-0.042*			
			(0.022)			
Subsector: Equipment and Machinery				0.035	0.015	0.075
(N=203)				(0.052)	(0.056)	(0.060)
Subsector: Food and Beverage				0.087*	0.062	0.063
(N=268)				(0.049)	(0.053)	(0.056)
Subsector: Paper, wood, printing and furniture				0.092*	0.066	0.066
(N=262)				(0.049)	(0.053)	(0.056)
Subsector: Retail Trade				0.012	-0.005	0.001
(N=480)				(0.045)	(0.047)	(0.051)
Subsector: Textile and clothing				0.069	0.041	0.007
(N=155)				(0.056)	(0.059)	(0.063)
Subsector: Wholesale trade				0.025	-0.007	0.006
(N=485)				(0.045)	(0.048)	(0.051)
Number of Relationships					0.002	0.001
					(0.002)	(0.002)
Firm age						0.000
						(0.001)
Constant	0.497***	0.440***	0.469***	0.413***	0.441***	0.418***
	(0.019)	(0.040)	(0.043)	(0.055)	(0.059)	(0.063)
Observations	2,024	2,024	2,024	2,024	1,790	1,534
R-squared	0.004	0.004	0.005	0.008	0.006	0.006

Note. The table reports results of regression where the dependent variable is a variable that takes a value of one if the firm participated in the follow-up, and zero otherwise. Number of Relationships is the number of supplier and customer firms that the firm has. Robust standard errors in parenthesis. The firm in the subsector "Other Store Retailing" is included in "Retail Trade" as there is only one firm belonging to that group.

Table A-4: Heterogeneous Treatment Effects: Firm Characteristics

(a) Expectations

	$Posterior^{mean}$				$Posterior^{uncertainty}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T_1 \times Prior \times H$	0.070	0.020	0.003	-0.076	0.103**	0.007	0.060	-0.012
	(0.047)	(0.018)	(0.066)	(0.101)	(0.052)	(0.017)	(0.066)	(0.094)
$T_2 \times Prior \times H$	0.009	0.019**	-0.050	0.141	-0.040	-0.010	-0.062	-0.060
	(0.056)	(0.008)	(0.094)	(0.124)	(0.054)	(0.009)	(0.063)	(0.107)
Heterogeneity, H	Employment	Market Share	Age	Manufacturing	Employment	Market Share	Age	Manufacturing
N	505	275	419	505	513	280	427	513

(b) Actions

	Price				Employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T_1 \times Plan \times H$	-0.080	-0.005	-0.081	0.087	0.197**	0.230**	-0.282	-0.050
	(0.080)	(0.051)	(0.105)	(0.154)	(0.084)	(0.116)	(0.186)	(0.300)
$T_2 \times Plan \times H$	0.167**	0.030**	-0.028	0.041	0.133	0.002	0.159	-0.303
	(0.071)	(0.012)	(0.105)	(0.172)	(0.184)	(0.051)	(0.180)	(0.341)
Heterogeneity, H	Employment	Market Share	Age	Manufacturing	Employment	Market Share	Age	Manufacturing
N	506	280	423	506	511	284	428	511

	Investment				Wages			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T_1 \times Plan \times H$	0.037	0.014	-0.032	0.132	0.014	-0.004	0.037	-0.006
	(0.074)	(0.015)	(0.131)	(0.170)	(0.036)	(0.003)	(0.051)	(0.070)
$T_2 \times Plan \times H$	-0.054	-0.015	0.131	0.062	-0.045	-0.002	-0.019	-0.013
	(0.067)	(0.013)	(0.083)	(0.137)	(0.033)	(0.003)	(0.035)	(0.045)
Heterogeneity, H	Employment	Market Share	Age	Manufacturing	Employment	Market Share	Age	Manufacturing
N	512	282	429	512	511	281	428	511

Note. Panels (a) and (b) extend the regressions of equations (1) and (2), respectively, to include an interaction of each term with variable H, for the sample of connected firms. Each column uses a different characteristic of the main firm for H, as labeled (log employment, market share, log firm age, and a dummy equal to one if in manufacturing). Only the triple interaction terms are displayed, which identifies the effect of H on the correlation of the posterior with the prior, in the case of Panel (a), and the correlation of the action with the plan, in the case of Panel (b). Standard errors are displayed in parentheses.

Table A-5: Heterogeneous Spillover Effects on Actions: Network Characteristics

	Price			Investment		
	(1)	(2)	(3)	(4)	(5)	(6)
$T_1 \times Plan \times H$	-0.194	-0.014**	-0.030	0.077	-0.006	-0.110
	(0.158)	(0.007)	(0.158)	(0.186)	(0.008)	(0.124)
$T_2 \times Plan \times H$	-0.083	0.014*	0.090	0.189	0.004	-0.163
	(0.163)	(0.008)	(0.121)	(0.132)	(0.009)	(0.125)
Heterogeneity, H	Upstream	Exp. Share	N connections	Upstream	Exp. Share	N connections
N	506	357	377	512	360	383

	Employment			Wages		
	(1)	(2)	(3)	(4)	(5)	(6)
$T_1 \times Plan \times H$	-0.687***	0.024***	0.029	-0.019	-0.004	-0.031
	(0.191)	(0.007)	(0.283)	(0.064)	(0.003)	(0.031)
$T_2 \times Plan \times H$	-0.485	0.009	0.217	0.080*	-0.001	-0.073
	(0.321)	(0.026)	(0.277)	(0.047)	(0.003)	(0.048)
Heterogeneity, H	Upstream	Exp. Share	N connections	Upstream	Exp. Share	N connections
N	511	356	385	511	358	385

Note. The specifications extend the regression of equation (2) to include an interaction of each term with variable H, for the sample of connected firms. Each column uses a different characteristic of the main firm for H, as labeled (a dummy equal to one if the customer, share of sales to or expenditure on the connected firm, and number of customers or suppliers — if they are a supplier or customer, respectively, in the latter two). Only the triple interaction terms are displayed, which identifies the effect of H on the correlation of the action with the plan. Standard errors are displayed in parentheses.

Table A-6: Causal Effect of Expectations on Actions, Pooled across Main and Connected Firms

	Price	Investment	Employment	Wage
	(1)	(2)	(3)	(4)
$Posterior^{mean}$	0.275***	0.053	0.916***	-0.001
	(0.084)	(0.142)	(0.299)	(0.016)
$Posterior^{uncertainty}$	-0.313***	-0.632***	-0.792***	0.005
	(0.042)	(0.063)	(0.129)	(0.008)
$Action^{main} \times 1[connected]$	0.352*	0.441***	0.071	0.757
	(0.191)	(0.097)	(0.078)	(0.564)
Observations	938	930	933	931
F(mean)	106.3	121.7	121.2	100.1
F(uncertainty)	451.2	540.7	463.8	458.5
F(action)	24.4	39.5	15.1	0.8

Note. The table reports results of equation (3), where the outcome variables are actions that the firm took in the three months before the follow-up survey. Those actions are the change in prices (column (1)), change in investment (column (2)), change in employment (column (3)), and change in wages (column (4)). $Posterior^{mean}$ is the GDP forecast of the firm in the follow up period. $Posterior^{uncertainty}$ is the uncertainty about the GDP forecast of firm i in the follow-up period, measured as the absolute value of the distance between the most and least likely scenario. $Action^{main} \times 1[connected]$ is the action of the main firm in the follow-up period, which is only present for connected firms. Variables not shown but included in the specification: $Plan$ is the plan that the firm had in the baseline survey for the next three months; $Prior^{mean}$ is the GDP forecast of the firm in the baseline period before receiving the treatment, and $Prior^{uncertainty}$ is the uncertainty forecast before the treatment. We instrument the posterior variables with the priors interacted by the treatment dummy. For connected firms, we also instrument the corresponding action of the main firm with the plan interaction by the treatment dummy. The first stage F-statistics are shown at the end of the table. Robust standard errors are shown in parentheses.

Table A-7: Decomposing the Spillover Effects on Actions

	Price		Investment		Employment		Wages	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Posterior^{mean,main}$	0.787***		0.203		2.242***		-0.011	
	(0.212)		(0.339)		(0.863)		(0.015)	
$Posterior^{uncertainty,main}$	-0.125		-0.332*		0.728*		0.035*	
	(0.095)		(0.172)		(0.424)		(0.019)	
$Action^{price,main}$	0.119	0.821**	0.310	1.555*	2.800**	2.709**	0.033	-0.035
	(0.280)	(0.407)	(0.428)	(0.796)	(1.233)	(1.180)	(0.024)	(0.032)
$Action^{emp,main}$	-0.064	-0.133	-0.094	-0.310	-0.560	-0.479	-0.009	0.004
	(0.089)	(0.111)	(0.128)	(0.225)	(0.386)	(0.348)	(0.009)	(0.008)
$Action^{invest,main}$	0.117	0.210**	0.321***	0.440***	0.565	0.366	0.024	0.009
	(0.079)	(0.091)	(0.113)	(0.163)	(0.355)	(0.240)	(0.015)	(0.011)
$Action^{wage,main}$	-4.133	-7.941	-2.872	-14.872	-25.081	-21.243	-0.138	0.403
	(3.945)	(6.865)	(5.868)	(14.461)	(17.584)	(20.327)	(0.435)	(0.550)
Observations	323	344	323	344	322	343	323	344
F(mean)	53.3		53.3		53.8		53.3	
F(uncertainty)	235.7		235.7		237.1		235.7	
F(price)	21.6	21.9	21.6	21.9	21.6	21.9	21.6	21.9
F(employment)	7.0	9.1	7.0	9.1	6.9	9.0	7.0	9.1
F(investment)	44.2	42.9	44.2	42.9	44.7	42.6	44.2	42.9
F(wage)	0.7	1.1	0.7	1.1	0.7	1.0	0.7	1.1

Note: The table reports results on a variant of regression (4), where the outcome variables are now the actions in the follow-up of the connected firm, with the action labeled in the column header. The coefficients are shown for the posteriors and actions in the follow-up of the main firm, which are instrumented by the treatment interacted with the main firm priors and plans, respectively. The first stage F-statistics are shown at the end of the table. In all specifications, we control for the plans of both firms, and in odd-numbered columns we control for the priors of the main firm. Robust standard errors are shown in parentheses.

Table A-8: Treatment Effect on Frequency & Content of Communication

	(1) GDP Comm. Comm. > 0	(2) Product Comm. Freq. $<$ Quarter	(3) Industry Comm. Freq. $<$ Quarter	(4) Economy Comm. Freq. $<$ Quarter
T_1	0.498***	0.066*	0.021	0.068
	(0.048)	(0.027)	(0.045)	(0.053)
T_2	0.423***	0.076**	0.059	0.039
	(0.052)	(0.026)	(0.043)	(0.053)
Control Mean	0.351	0.904	0.806	0.272
Observations	456	478	448	451

Notes: This table reports OLS regressions on the sample of main firms. The independent variables are dummies for the treatment group. The dependent variables are dummies as follows. In column (1), equal to one if communication about GDP with the connected firm reported in the follow-up is non-zero. In columns (2), (3), and (4), equal to one if communication frequency reported in the follow-up is less than quarterly for product, industry, and economy-wide topics, respectively. Robust standard errors are shown in parentheses.

Table A-9: Effect of Actions of the Connected Firm and Expectations Control

	Price		Investment		Employment		Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Posterior^{mean}	0.374***		0.116		0.515		-0.006	
	(0.129)		(0.219)		(0.413)		(0.014)	
Posterior^{uncertainty}	-0.322***		-0.585***		-1.033***		0.013	
	(0.093)		(0.119)		(0.262)		(0.009)	
Action^{main}	0.322*	1.007***	0.263**	0.676***	0.182	0.881***	0.855	0.809
	(0.182)	(0.135)	(0.105)	(0.097)	(0.239)	(0.230)	(0.818)	(0.816)
Plan	0.744***	0.784***	0.475***	0.438***	0.881***	0.874***	1.003***	1.002***
	(0.054)	(0.058)	(0.087)	(0.103)	(0.062)	(0.082)	(0.016)	(0.016)
Plan^{main}	-0.236	-0.832***	-0.097	-0.265***	-0.131	-0.679***	-0.861	-0.814
	(0.189)	(0.166)	(0.079)	(0.096)	(0.241)	(0.254)	(0.821)	(0.823)
Prior^{mean}	-0.178*		-0.025		-0.285		-0.006	
	(0.100)		(0.179)		(0.344)		(0.007)	
Prior^{uncertainty}	0.211**		0.553***		0.998***		-0.009	
	(0.084)		(0.101)		(0.243)		(0.007)	
Constant	0.495**	0.219*	0.348	0.554**	-0.226	0.683	0.015	-0.007
	(0.247)	(0.119)	(0.448)	(0.226)	(0.678)	(0.472)	(0.029)	(0.012)
Observations	212	212	207	207	209	209	208	208
R-squared	0.649	0.467	0.446	0.072	0.630	0.400	0.975	0.975
F (mean)	41.08		40.41		36.82		36.47	
F (uncert)	93.76		97.42		94.62		107.8	
F (action)	23.49	34.17	38.59	74.19	9.527	18.10	0.549	0.757

Notes: The table reports results of regression 3, where the outcome variables are actions the firm took in the three months before the follow-up survey, for the connected firms that are customers. Those actions are the change in prices (columns 1-2), change in investment (columns 3-4), change in employment (columns 4-5), and change in wages (columns 7-8). $Plan$ ($Plan^{main}$) is the plan the connected (main) firm had in the baseline survey for the next three months. $Action^{main}$ is the action (as shown in the heading of the column) of the main firm and $Plan^{main}$ is the plan for the action in the baseline. $Posterior^{mean}$ is the GDP forecast, and $Posterior^{uncertainty}$ is the uncertainty about the GDP forecast of the connected firm in the follow-up period. Posteriors are instrumented with the treatment and the interaction of priors with the treatment dummy, and actions are instrumented with the treatment and the interaction of plan with the treatment. Robust standard errors are shown in parentheses.

B Model

B.1 Additional Details

Matrix structure in the optimal price equation. The optimal price setting equation is

$$\boldsymbol{p}_t = \Delta\left(\boldsymbol{\kappa} y_t + \beta\Omega\widetilde{\mathbb{E}}_t\left[\boldsymbol{p}_{t+1}\right] + \Omega\boldsymbol{p}_{t-1}\right), \tag{B.1}$$

where the expressions for $\boldsymbol{\kappa}$, Ω, and Δ are given by:

$$\begin{aligned}
\boldsymbol{\kappa} &= \varphi \frac{\Phi(I - IO\Phi)^{-1}\boldsymbol{\alpha}}{1 - \boldsymbol{\psi}\Phi(I - IO\Phi)^{-1}\boldsymbol{\alpha}}, \\
\Omega &= I - \left[\Phi(I - IO\Phi)^{-1} - \frac{\boldsymbol{\kappa}\boldsymbol{\psi}'}{\varphi}\left((I - IO)^{-1} - \Phi(I - IO\Phi)^{-1}\right)\right](I - IO), \\
\Delta &= (I + \beta\Omega)^{-1},
\end{aligned} \tag{B.2}$$

and $IO \equiv [\iota_{ij}]$ is the input-output matrix; $\boldsymbol{\alpha}$ is the vector of labor shares; and $\boldsymbol{\psi}$ is the vector of consumption shares. As in Rubbo (2023), $\Phi = diag(\hat{\phi}_1, \hat{\phi}_2, \hat{\phi}_3)$ where $\hat{\phi}_i = \frac{\phi_i(1-\beta(1-\phi_i))}{1-\beta(1-\phi_i)}$ with ϕ_i being the Calvo probability that firm i adjusts its price in a given quarter. Finally, φ is a scalar in the Phillips curve slope that captures labor supply elasticity.

Simulation exercise. We simulate the price response vector across firms to a unit information treatment over different values of the supplier's input share, $\iota_{21} \in \{0.1, 0.2, ..., 1\}$, and the customer's input shares from the supplier and the rest of the network, $\iota_{32} \in \{0, 0.1, 0.2, ..., 1 - \alpha_3\}$. In terms of calibration, we set α_3 equal to 0.38, the average labor share cost reported from customer firms. The structure of the network implies that $\alpha_1 = 1$, $\alpha_2 = 1 - \iota_{21}$, and $\iota_{31} = 1 - \iota_{32} - \alpha_3$. In terms of the price adjustment probabilities, we set the probability that the supplier and customer firms change their price in any given quarter equal to approximately 0.63 and 0.66, respectively, consistent with the average frequency of price adjustment of treated supplier and treated customer firms in our sample, respectively.[30] We set the adjustment probability of firm 1 equal to approximately 0.61 to match the average probability that supplier firms in the control group change the price within a quarter—note that firm 1 in the model does not represent the control group in

[30]Firms report whether they change the price of their main product daily, weekly, monthly, quarterly, semi-annually, annually, or less than annually. We then set the probability of price adjustment at the quarterly frequency equal to 100% if the firm adjusts the price at a quarterly or higher frequency, 50% if the firm adjusts the price semi-annually, and 25% if the firm adjusts the price annually. For the firms that adjust the price less than annually, we assume they do so every 6 quarters, which places their probability of price adjustment equal to about 16.7%.

our experiment; since we do not observe the "rest of the network" to which our supplier-customer pairs are connected, we proxy its price flexibility with that of suppliers in the control group. Next, we set the gain parameter from the information treatments equal to $g = 0.6995$ for all treated firms, computed as the average treatment effect of growth expectations for the treated firms relative to the control firms as in Weber et al. (2025).[31] Finally, we set the discount factor β equal to 0.9975 and $\varphi = 3$ as in Rubbo (2023), and allocate equal consumption shares to firms $\boldsymbol{\psi} = \mathbf{1}/3$.

B.2 Proofs

Next, we formally prove Proposition 1, Corollary 2, and Proposition 2. Corollary 1 follows directly from Proposition 1 in the case of price responses and from equation (11) in the case of expectations responses; Corollary 3 follows directly from Proposition 2.

B.2.1 Proof of Proposition 1

The optimal price vector depends on the current output growth, vector of signals, vector of ambiguity, and the vector of past prices. Hence, we guess the following solution:

$$\boldsymbol{p}_t = M_s \boldsymbol{s}_t + M_y \boldsymbol{y}_t + M_a \boldsymbol{a}_t + M_p \boldsymbol{p}_{t-1},$$

implying that expectations about the price vector in $t+1$ are

$$\widetilde{\mathbb{E}}_t \boldsymbol{p}_{t+1} = M_y \widetilde{\mathbb{E}}_t \boldsymbol{y}_{t+1} + M_p \boldsymbol{p}_t = -M_y \mathcal{C}(I - G)\boldsymbol{a}_t + M_y \mathcal{C} G \boldsymbol{s}_t + M_p \boldsymbol{p}_t.$$

[31] Specifically, using the point estimates of β, θ^1 and θ^2 reported in column (1) of Tables 1 and 2, we average across the four values of $\hat{\theta}/\hat{\beta}$.

Plugging expectations into the optimal price equation and letting $K = diag(\boldsymbol{\kappa})$, we have

$$\begin{aligned}
\boldsymbol{p}_t &= \Delta K \boldsymbol{y}_t + \Delta\Omega \boldsymbol{p}_{t-1} + \beta\Delta\Omega \left[-M_y \mathcal{C}(I-G)\boldsymbol{a}_t + M_y \mathcal{C} G \boldsymbol{s}_t + M_p \boldsymbol{p}_t\right] \\
&= (I - \beta\Delta\Omega M_p)^{-1} \left[\Delta K \boldsymbol{y}_t + \Delta\Omega \boldsymbol{p}_{t-1} + \beta\Delta\Omega \left(-M_y \mathcal{C}(I-G)\boldsymbol{a}_t + M_y \mathcal{C} G \boldsymbol{s}_t\right)\right].
\end{aligned}$$

From here, it follows that

$$\begin{aligned}
M_p - \beta\Delta\Omega M_p^2 &= \Delta\Omega \\
M_y &= (I - \beta\Delta\Omega M_p)^{-1}\Delta K \\
M_a &= -\beta(I - \beta\Delta\Omega M_p)^{-1}\Delta\Omega M_y \mathcal{C}(I-G) \\
M_s &= \beta(I - \beta\Delta\Omega M_p)^{-1}\Delta\Omega M_y \mathcal{C} G
\end{aligned} \tag{B.3}$$

It is straightforward to see from the first equation above that $M_s = \beta M_p M_y \mathcal{C} G$ and $M_a = -\beta M_p M_y \mathcal{C}(I-G)$. To ease notation, we set $M = M_p \times M_y$. To solve for M_p, we rely on Theorem 3.5 in Uhlig (2001); to ensure that price dynamics are stable, we only consider the solution for M_p whose eigenvalues are within the unit circle. To prove that all the elements of matrix M are positive, we first prove the following lemma:

LEMMA 1. *All the elements of matrix M_p are positive and less than unity, and the sum of elements in each row of M_p equals 1.*

To prove the lemma above, we show that M_p and Ω share the same eigenvectors. Recall that M_p is the solution to the quadratic matrix equation: $M_p^2 - \left(\Omega^{-1}/\beta + I\right) M_p + I/\beta = \mathbf{0}_N$. Let

$$\Xi = \begin{bmatrix} \Xi_{11} & \Xi_{12} \\ \Xi_{21} & \Xi_{22} \end{bmatrix} = \begin{bmatrix} \Omega^{-1}/\beta + I & -I/\beta \\ I & \mathbf{0}_N \end{bmatrix}$$

Let λ be an eigenvalue of Ξ, then the eigenvector associated with it is the vector

$X = \begin{bmatrix} X_1 & X_2 \end{bmatrix}'$, that is,

$$(\Xi - \lambda I)X = 0 \Rightarrow (\Xi_{11} - \lambda I)X_1 = X_2/\beta,\ X_1 = \lambda X_2$$

Hence, the eigenvector associated with λ is $X = \begin{bmatrix} \lambda X_2 & X_2 \end{bmatrix}'$. Therefore,

$$(\Xi_{11} - \lambda I)X_1 - X_2/\beta = 0 \iff (\Omega^{-1} - \underbrace{(\beta\lambda - \beta + 1/\lambda)}_{\text{e-value of } \Omega^{-1}} I)X_2 = 0$$

Uhlig (2001) shows that the eigenvector of M_p is given by X_2. Ω^{-1} and Ω share the same eigenvectors and, as a result, it follows that M_p and Ω also share the same eigenvectors. The largest eigenvalue of Ω is 1; the eigenvector associated with it is $e = \mathbf{1}_N$. It follows that e is also an eigenvector of M_p, hence $M_p e = e$, implying that the sum of each row of M equals 1 and that 1 is an eigenvalue of M_p. To guarantee a stable solution, it has to be that the remaining eigenvalues of M_p are within the unit circle. By the Gershgorin circle theorem, each eigenvalue λ_i of M_p has to be within the following range $\left[1 - \sum_{j=1}^N m_{ij}^p - \sum_{j=1}^N |m_{ij}^p|, 1 - \sum_{j=1}^N m_{ij}^p + \sum_{j=1}^N |m_{ij}^p|\right]$. The bounds cannot exceed 1 or -1, implying that $\sum_{j=1}^N m_{ij}^p = \sum_{j=1}^N |m_{ij}^p|$, and that each element of M_p is positive.

It is easy to see that $M_p M_y = M_p^2 \Omega^{-1} K$, where all the diagonal elements in K are positive. Since M_p and Ω^{-1} are stochastic matrices, it follows that $M_p^2 \Omega^{-1}$ is also a stochastic matrix and that all the elements in M are positive.

B.2.2 Proof of Corollary 2

The response of the price vector is given by $\frac{\partial \boldsymbol{p}_t}{\partial s_{jt}} = \beta g M_p^2 \Omega^{-1} diag(\boldsymbol{\kappa}) \mathcal{C}_{:j}$. Absent communication, the response is $\beta g \boldsymbol{\kappa}_j (M_p^2 \Omega^{-1})_{:,j}$; hence, price dispersion depends on the dispersion of the elements in the j^{th} column of $M_p^2 \Omega^{-1}$. From the proof of Proposition 1, $M_p - \beta \Delta \Omega M_p^2 = \Delta \Omega$; pre-multiplying this expression by Δ^{-1}, eigendecomposing M_p and Ω, and using the fact that M_p and Ω share the same eigenvectors, we have that

$$(I+\beta Q\Lambda_\Omega Q^{-1})Q\Lambda_p Q^{-1}-\beta Q\Lambda_\Omega\Lambda_p^2 Q^{-1} = Q\Lambda_\Omega Q^{-1} \Rightarrow \beta\Lambda_\Omega\Lambda_p^2-(I+\beta\Lambda_\Omega)\Lambda_p-\Lambda_\Omega = \mathbf{0}_{N,N},$$

where Q is the matrix containing the eigenvectors; Λ_Ω and Λ_Ω are the diagonal matrices containing the eigenvalues of M_p and Ω, respectively. Pinning down the eigenvalues of M_p is equivalent to solving for the roots of N quadratic polynomials. It is easy to see that 0 is an eigenvalue of M_p only if 0 is also an eigenvalue of Ω, which cannot happen since Ω is invertible. As a result, 0 is not an eigenvalue of $M_p^2\Omega^{-1}$, thus the elements in any j^{th} column of $M_p^2\Omega^{-1}$ are different from one another. Therefore, absent communication there is always dispersion in the initial response of prices to the information treatment.

The response of the price vector under even communication is given by

$$\frac{\partial \boldsymbol{p}_t}{\partial s_{jt}} = \beta g \left[\sum_j (M_p^2\Omega^{-1})_{1j}\boldsymbol{\kappa}_j \quad \dots \quad \sum_j (M_p^2\Omega^{-1})_{Nj}\boldsymbol{\kappa}_j\right]',$$

where $\sum_j (M_p^2\Omega^{-1})_{ij} = 1$, $\forall i$. From above, we know that the elements in any column of $M_p^2\Omega^{-1}$ are distinct from one another. Hence, any dispersion in the initial response of the price vector has to be due to heterogeneous Phillips curve slopes. If all firms share the same Phillips curve slope κ, then the initial response of any price would be $\beta g\kappa$.

B.2.3 Proof of Proposition 2

From Proposition 1 in the paper, the vector of prices converges to

$$\lim_{h\to\infty} \boldsymbol{p}_{t+h} = \beta g_j \lim_{h\to\infty} M_p^{h+1} M_y \mathcal{C}_{:,j} = \beta g_j \lim_{h\to\infty} M_p^{h+2}\Omega^{-1} diag(\boldsymbol{\kappa})\mathcal{C}_{:,j}, \tag{B.4}$$

where the second equality follows from the fact that $M_p M_y = M_p^2\Omega^{-1}diag(\boldsymbol{\kappa})$. As shown in the proof of Proposition 1, M_p and Ω^{-1} share the same eigenvectors, and the absolute value of all the eigenvalues of M_p, other than the unit one, lie within the unit circle. Hence, the eigendecomposition of $M_p^{h+2}\Omega^{-1}$ as h approaches ∞ is given by

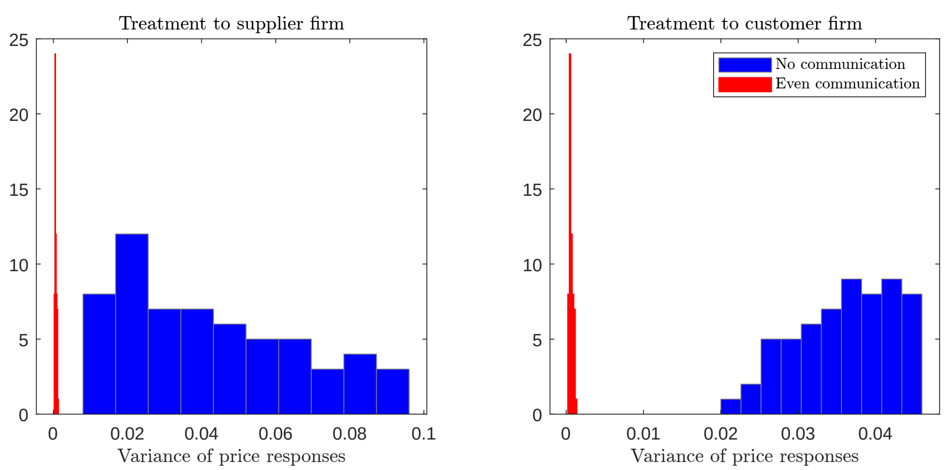
$$\lim_{h\to\infty} M_p^{h+2}\Omega^{-1} = Q\begin{bmatrix} 1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} Q^{-1} = \begin{bmatrix} Q_{11}Q_{1:}^{-1} & Q_{12}Q_{1:}^{-1} & \dots & Q_{1N}Q_{1:}^{-1} \end{bmatrix}'$$

The eigenvector of M_p associated with the unit eigenvalue is $Q_{1:} = \mathbf{1}$, whereas $Q_{1:}^{-1}$ is the eigenvector of Ω' associated with its unit eigenvalue – since M_p, Ω, and Ω^{-1} share the same eigenvectors. Rubbo (2023) proves in the Appendix that $Q_{1:} = \boldsymbol{\lambda}(I - \Phi)\Phi^{-1}$, so that $\Omega' Q_{1:} = Q_{1:}$.

B.3 Additional Results from the Model

Within-network initial price response variation. Figure A-3 shows the histogram of the within-network variance of the initial price responses to a treatment of higher uncertainty.

Figure A-3: Distribution of Within-Network Price Variance after Treatment of Higher Uncertainty



Note: Distribution of the variance of initial price responses across networks when the treated firm is the supplier (left panel) and when the treated firm is the customer (right panel). In red: even communication; in blue: no communication.

Relationship between the price of the treated and that of the connected firm. We estimate the change in the price of the connected firm that is associated with a change in the price of the main (treated) firm in the model simulations and survey data. In the survey data, we instrument the price change of the main firm with interactions between the treatment dummy and the price plan that the firm had. In particular, we estimate β_1 and β_2 in the following regression

$$Price^{connected}_{j-i} = \beta_1(Price^{treated}_i|\text{Talk GDP}_{j-i}) + \beta_2(Price^{treated}_i|\text{No Talk GDP}_{j-i}) + X_{it}\delta' + \varepsilon_i,$$

Vector X_{it} embeds firm i and j's planned price changes. Importantly, we separate the effect between the firms that communicated at least once about GDP and the firms that did not. While communication is also affected by the treatment, potentially biasing these estimates, we see these results as suggestive evidence of the model mechanisms.

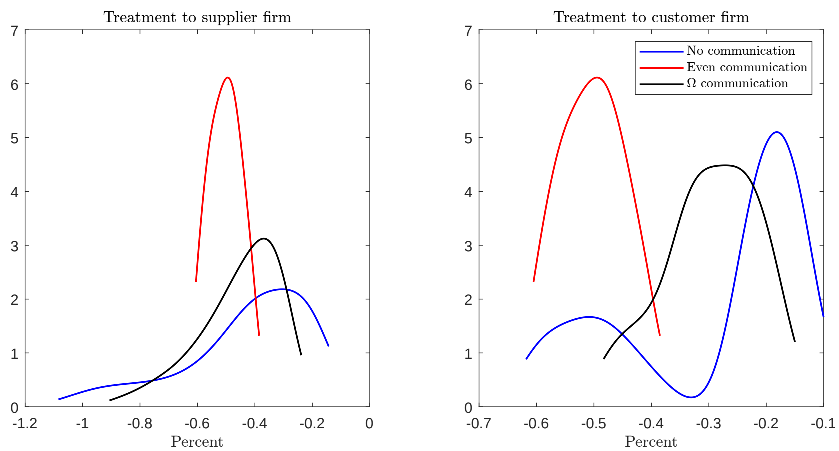
Table A-10: Price Pass-through from Treated to Connected Firms

	(1)	(2)	(3)	(4)
$Price^{treated}\|Talk\ GDP$	0.816***		0.810***	
	(0.158)		(0.224)	
$Price^{treated}\|No\ Talk\ GDP$	0.261		0.631***	
	(0.179)		(0.205)	
$Price^{treated}\|Even\ Comm$		1.020***		0.980***
		(0.004)		(0.004)
$Price^{treated}\|No\ Comm$		0.348***		0.508***
		(0.005)		(0.009)
Type	Supplier	Supplier	Customer	Customer
Shock to	Customer	Customer	Supplier	Supplier
Data	Survey	Model	Survey	Model
F (Talk)	17.89		15.34	
F (No Talk)	32.93		112	
Observations	181	180	164	180
R-squared	0.513	0.820	0.441	0.662

Note: The table reports results of a regression that estimates the empirical price pass-through from the treated firm to the connected firm (columns (1) and (3)), and the equivalent regression in the model (columns (2) and (4)). We instrument both $Price^{treated}|Talk\ GDP$ and $Price^{treated}|No\ Talk\ GDP$ with the price change plans of the treated firm, interacted by the treatment, the treatment indicator and the interaction with whether they talked or not. We control for the treated and connected firms' plans. Robust standard errors in all regressions.

Alternative communication matrix. Figure A-4 shows that in the case of $\mathcal{C} = \Omega$, the price responses are amplified relative to the no communication scenario, but not by as much as they are under even communication. Similar to the case of no communication, Ω communication implies that the price responses are bigger when the treatment originates from the supplier firm than when they come from the customer firm.

Figure A-4: Distribution of the Impact on Prices after Treatments of Higher Uncertainty



Note: Distribution of price changes across all three firms when the treated firm is the supplier (left panel) and when the treated firm is the customer (right panel). In red: even communication; in blue: no communication; in black: Ω communication.

C Design Details

C.1 Sample

Our population in the survey is quite representative of the firms in New Zealand. Panel A in Table A-1 presents the total number and percentage of firms in manufacturing and trade (wholesale and retail). As per Statistics New Zealand, there are slightly over 31,000 firms in manufacturing, retail, and wholesale trade. More than half the firms in these industries are small firms employing fewer than six employees. The population of firms in this survey is drawn from these industries, and we use employment size distribution as the benchmark to control for sample representation. Our survey maintains fairly similar proportions of firms at each firm size distribution, that is, firms with fewer than 5 employees,6-19 employees, 20-49 employees, and at least 50 employees.

It is not uncommon in surveys to attain varying response rates from firms across different industries. One of the objectives of the survey was to achieve higher response rates from firms that employ at least six employees. Firms that are too small in size are quite vulnerable and their business continuity is always questionable. Furthermore, during the process of developing the population data, it was evident that very small firms tend to change their input suppliers quite frequently; this is not ideal for our RCT exercise. In this survey, therefore, a lot of focus was given to firms that employ at least six employees. The response rates for different employment size groups are also reported in Panel C and D. The overall response rate is around 13 percent for the main wave and around 50 percent for the follow-up wave. With the assistance of survey recruitment specialists, the survey retained nearly half the firms to participate in the follow-up wave.

The participants in the survey are managers or directors of the firm. One of the criteria for participant recruitment was that the manager or director must play an integral role in the firm in setting product prices and wages, and also be an influential figure in investment and employment decisions. This criterion was applied to recruit participants for the population database compiled by New Zealand Market Research and Surveys Limited.

D Survey

D.1 Pre-Survey Information

The survey company (New Zealand Market Research and Surveys Limited) provided some firm characteristics that they collected independently of, and months before, our survey. These include employment, inventory share from main supplier, number of customers, and number of suppliers.

A few days before the baseline of our survey, the survey company verified supplier and customer identification. Specifically:

Ask this question to customer/main supplier firm: Your firm is listed in the database at New Zealand Market Research and Surveys Limited. The database indicates that XXX [firm name] is your customer/main supplier of the main product line. Is this information correct?

[1]Yes, [2]No

D.2 Baseline Survey

Section A. Firm Characteristics

1 **How many years old is the firm?**

Answer: ________ years

2 **How many workers are employed in this firm?**

Answer: ________workers

3 **Out of the total revenue of the firm, what fraction is used for compensation of all employees and what fraction is used for the costs of materials and intermediate inputs (raw materials, energy inputs, etc...)?**

Share of revenues: Labor cost ________ % , Cost of materials ________ %

4 **For its main product line, what is the firm's current market share?**
Answer: ________ %

5 **How many weeks ago did your firm change the price of the main product?**
Answer: ________ Weeks ago.

6 **Using the following frequencies, please identify how often this firm (formally) changes the price of its main product:**

[i] Daily, [ii] Weekly, [iii]Monthly,[iv] Quarterly, [v] Semi-annually, [vi] Annually, [vii] Less frequently than annually

Section B. Manager Characteristics

7 **How many years of work experience do you have at this firm:** Answer: ________ years.

8 **What is your highest educational qualification?**

[a]Less than high school, [b] High school diploma, [c] Some college or Associate degree, [d] College Diploma, [e] Graduate Studies (Masters or PhD)

Section C. Macroeconomic Expectations

9 **What do you think will be the annual growth rate of real GDP in New Zealand in twelve months?**
Answer: ________ % per year.

10 **Could you provide us with an approximate range of what you think annualized real GDP growth in New Zealand will be over the next 12 months?**
Between ________ % per year (lowest forecast) and ________ % per year (highest forecast).

Section D. Predictions

11 **Over the next 3 months, by how much (in % changes relative to current level) do you expect to change:**

(a) The price of your main product: __________ %

(b) Investment in capital goods: __________ %

(c) Employment at your firm: __________ %

(d) Average wages: __________ %

Section E. Information Treatment

Group 0 (Control): No information.
Group 1 (Mean treatment): We are going to give you information from a group of leading experts about the New Zealand economy. According to Consensus Economics, a leading professional forecaster, the average prediction among professional forecasters is that the real GDP will grow by 2.3% in 2025.
Group 2 (Uncertainty Treatment): We are going to give you information from a group of leading experts about the New Zealand economy. According to Consensus Economics, a leading professional forecaster, the difference between the lowest and highest predictions of real GDP growth is 2.2 percentage points for 2025.

12 **Please let me know what you perceive as the most pessimistic, the most likely, and most optimistic real GDP growth rate for New Zealand over the next 12 months. What do you think the lowest annualized real GDP growth rate might be for this time period, what do you think the most likely might be, and what do you think the highest might be? (please provide an answer as % per year).**

(a) Lowest real GDP growth rate:__________ % per year

(b) Most likely GDP growth rate:__________ % per year

(c) Highest real GDP growth rate:__________ % per year

Thank you very much for your participation.

D.3 Follow-up Survey

NB: This survey is conducted approximately 3 months after the first interview.

Section A. Characteristics

1 **How many weeks ago did your firm change the price of main product?**
Answer: __________ Weeks ago.

Section B. Macroeconomic Expectations

2 **Please let me know what you perceive as the most pessimistic, the most likely, and most optimistic real GDP growth rate for New Zealand over the next 12 months. What do you think the lowest annualized real GDP growth rate might be for this time period, what do you think the most likely might be, and what do you think the highest might be? (please provide an answer as % per year).**

(a) Lowest real GDP growth rate:__________ % per year

(b) Most likely GDP growth rate:__________ % per year

(c) Highest real GDP growth rate:__________ % per year

Section C. Actions of firms

3 **Over the last 3 months, by how much (in % changes) did you change:**

(a) The price of your main product:__________ %

(b) Investment in capital goods:__________ %

(c) Employment at your firm:__________ %

(d) Average wages:__________ %

4 **What are the primary reasons behind your expectation of GDP growth and its range in question 2?**

Please select relevant options. Multiple answers are allowed.

(a) My customer/main supplier firm XXX changed fundamental factors (such as price, quantity, inputs), providing insights

(b) My customer/main supplier firm XXX directly shared information about GDP growth and uncertainty.

(c) Various other firms in your network changed fundamental factors or shared information.

(d) Public sources (such as government, central bank, news) of information.

(e) Other: Please specify __________

Section D. Supplier/Customer Characteristics

5 **What is your share of expenditure/sales to your customer/main supplier firm XXX?**

(a) Share of total expenditure: __________ % *If the respondent is a customer*

(b) Share of total sales:__________ % *If the respondent is the main supplier*

6 **In general, how often do you communicate with your customer/main supplier firm XXX?**

(a) About your product transactions

[i] Daily, [ii] Weekly, [iii]Monthly,[iv] Quarterly, [v] Semi-annually, [vi] Annually, [vii] Less frequently than annually

(b) About industry trends and conditions

[i] Daily, [ii] Weekly, [iii]Monthly,[iv] Quarterly, [v] Semi-annually, [vi] Annually, [vii] Less frequently than annually

(c) About economic trends and conditions

[i] Daily, [ii] Weekly, [iii]Monthly,[iv] Quarterly, [v] Semi-annually, [vi] Annually, [vii] Less frequently than annually

7 **In general, if you had to place a dollar value on the information that you acquire from your customer/main supplier firm XXX about product transactions, industry trends and conditions and economic trends and conditions each year, how much do you think that $ value would be? Please use minimum as $0 and maximum as $1000.**

(a) ________ $ per year for information on product transactions

(b) ________$ per year for information on industry trends and conditions

(c) ________$ per year for information on economic trends and conditions

Section E. Mechanisms for modeling

8 **What are the primary reasons you would share information about GDP growth and uncertainty with your customer/main supplier firm XXX?** *Multiple answers are allowed.*

(a) To reduce operational costs

(b) To comply with legal requirements

(c) To foster innovation and collaboration

(d) To gain a competitive advantage

(e) To foster trust

(f) To address common sectoral challenges

(g) I do not share information about GDP growth or uncertainty with my customer/main supplier firm XXX.

(h) Other: Please specify ____________

9 **If you currently have a pricing and quantity contract with your customer/main supplier firm XXX, when was this contract initiated?**

(a) Less than 2 month

(b) 2-3 months

(c) 3-4 months

(d) Greater than 4 months

(e) No current contract

10 **Over the last three months, how many times did you communicate with your customer/main supplier firm XXX about GDP?** Answer: ____________ times over the last three months.

Thank you very much for your participation.