Supply Chain Networks and the Macroeconomic Expectations of Firms*

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In a randomized control trial of customer-supplier firm pairs in New Zealand, we treat with information one firm in a pair and analyze its effects on expectations and actions of the directly treated firms (direct effect) and connected firms that did not directly receive information (spillover effect). We find strong spillover effects in expectations and actions. We show that the spillover effects on the connected firms' expectations are driven by inter-firm communication, as opposed to observable actions. We embed inter-firm communication along the supply chain in a New Keynesian pricing problem and discuss the macroeconomic implications of input-output network-specific communication.
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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 analysis of how these expectations are formed (Coibion and Gorodnichenko, 2015; Coibion et al., 2018a), and of what their effect is on individual decision-making (Coibion et al., 2020b; Georgarakos et al., 2024). Special interest has been placed on firms' decision-making given their price-setting power (Coibion et al., 2018b, 2020a), and the influence of aggregate uncertainty in shaping these decisions (Bloom et al., 2007; Bloom, 2009; Coibion et al., 2024; Kumar et al., 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, 2016; Carvalho et al., 2021; Ozdagli and Weber, 2023; Pasten et al., 2020), we investigate *how learning between firms along the supply chain shapes their macroeconomic expectations, and its consequences for their decision-making*.

We provide experimental evidence on the presence and prominence of information diffusion between firms, and reveal direct communication to be a central, yet unexplored, mechanism. This has potentially 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. Unlike standard shock propagation via prices or output—that flow asymmetrically upstream vs downstream (Acemoglu et al., 2016; Carvalho and Tahbaz-Salehi, 2019)—we find communication to be symmetric, reconfiguring our understanding of how shocks propagate through supply chains. We end the paper by embedding communication into a macroeconomic model to explore its aggregate implications.

We implemented a randomized controlled trial using a two-wave survey of 1,000 firm–firm pairs in New Zealand, where one firm was the primary supplier of the other. In the baseline wave, one firm in each treated pair received an information treatment consisting of official GDP growth forecasts—either the mean forecast or a measure of uncertainty. This design enables us to identify the causal spillover

effects on the other firm within the pair in the follow-up wave, conducted three months later to allow time for information diffusion.

Experimentally identifying firm spillover effects required overcoming substantial challenges. Both firm survey capabilities and supply chain network data are required, each of which are individually rare. Moreover, a paired-firm design compounds the already high attrition rates typical of firm surveys, as both firms need to remain in the survey. We are uniquely positioned to address these challenges: we combined the strong firm survey infrastructure in New Zealand with the collection of original firm-to-firm network data.

The provision of information caused both firms within the pair to update their expectations. The direct effects on the "main" firm that the treatment was applied to corroborates findings in the literature (Coibion et al., 2018b; Kumar et al., 2023).[1] The spillover effects on the "connected" firm that didn't directly receive the treatment, however, are novel. As expected, the connected firms' expectations show no change in the baseline wave, instead only updating in the follow-up wave, consistent with it taking time for the information to diffuse. Strikingly, the magnitude of the spillover effects are comparable to that of the direct effects. This implies that the information diffusion is strong, and suggests generally that the supply chain network is a highly relevant factor in the formation of macroeconomic expectations.

Given the effect on firm beliefs, we next see if this materialized into an effect on their decisions—prices, investment, employment, and wages. We find significant effects in the follow-up on *both* the directly treated and connected firms. The magnitudes of both are again similar, implying that there are large, real effects from the propagation of macroeconomic information along the supply chain. Specifically, using the variation induced by the treatment, a 1 p.p. increase in expected GDP growth increases firms' prices and employment by 0.28 and 0.92 p.p., compared to their plan three months ago. Likewise, a 1 p.p. increase in uncertainty (measured as the range across GDP growth scenarios) decreases prices, investment and employment by 0.31, 0.63 and 0.79 p.p. We find no effect on wages.

[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 et al., 2018b) and more generally (Candia et al., 2024; Song and Stern, 2024). For theoretical mechanisms rationalizing this inattention, see, for instance, Afrouzi and Yang (2018); Gabaix (2020); Sims (2003).

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 spillovers 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 about the main firm's beliefs, conceivably through communication. Second, in the follow up wave, 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 about GDP, compared to only 35% of control firms.

Third, we show that spillover effects are symmetric whether flowing upstream or downstream the supply chain, which is identified as we randomized whether the main firm is a customer or supplier in the pair. If learning were mediated exclusively through observing the actions of the main firms, one may expect asymmetric spillover effects given the asymmetric propagation via (for example) prices documented in the literature (Acemoglu et al., 2016; Carvalho and Tahbaz-Salehi, 2019). Consistent with communication underlying the spillover effects, we also find the reported levels of GDP communication to be symmetric. This is an interesting result more broadly as it suggests that firms are not engaging in strategic disclosure of information on GDP.

We end the paper with examining the potential macroeconomic implications by embedding communication into a New Keynesian production network model. We assume a standard social network learning process based on DeGroot (1974), where each firm forms its beliefs as an average of all its connections' beliefs, weighted by their intensity of communication. As a benchmark, motivated by our empirical evidence, we consider a *uniform communication* network where all firms communicate with each other symmetrically.

The model implies that, when firms receive a signal about future output growth, uniform communication tends to reduce the dispersion and persistence of *firm-level*

inflation relative to no communication.[2] The response of *aggregate* inflation under no communication is determined by the shocked firm's position in the supply chain, summarized by their Domar weight and Phillips curve slope, paralleling findings in the production network literature (Carvalho and Tahbaz-Salehi, 2019; Pastén et al., 2024). Under communication, these are no longer sufficient statistics: the response now also depends on the communication network. This shift is potentially substantive because communication transmits shocks symmetrically while standard price propagation—that underlie Domar weights and slopes of the Phillips curve—flows asymmetrically.

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 et al. (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 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 et al., 2018b, 2020a,b; Coibion and Gorodnichenko, 2025; Kumar et al., 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 et al. (2021), and Pellet and Tahbaz-Salehi (2023) incorporate higher order expec-

[2] In the Appendix, we use the model to explore the role of uncertainty about future growth for pricing decisions.

[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 et al., 2016; Jackson, 2008).

tations 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 et al., 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 and implemented a randomized controlled trial leveraging an information-based intervention. The key novelty of our design is that we partially observe—and exploit—the supply chain connections between firms; this data was unavailable in previous research. We constructed a sample of pairs of firms where one is the primary supplier of the other (according to expenditure share on intermediates), and developed the survey instrument to exploit this feature of the data.

The survey was conducted by New Zealand Market Research and Surveys Limited. This company surveys firms and records information about their business operations. Importantly, they also facilitated collection of the identities of a firm's major suppliers. The survey company's sample of firms are mostly in the manufac-

turing and trade sectors, employ at least three workers, and have an annual sales turnover of at least NZL $30,000. The company holds contact details for approximately 8,100 pairs of firms, which are representative of the population of firms in New Zealand in terms of industry and employment size (see Table A-1 and the Online Appendix C.1). We successfully recruited over 1,000 firm pairs to participate in our survey. 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 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 informa-

[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.

tion provided to the treatment group closely aligns with established protocols in the existing literature (see Weber et al. 2025 for a review). 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.*

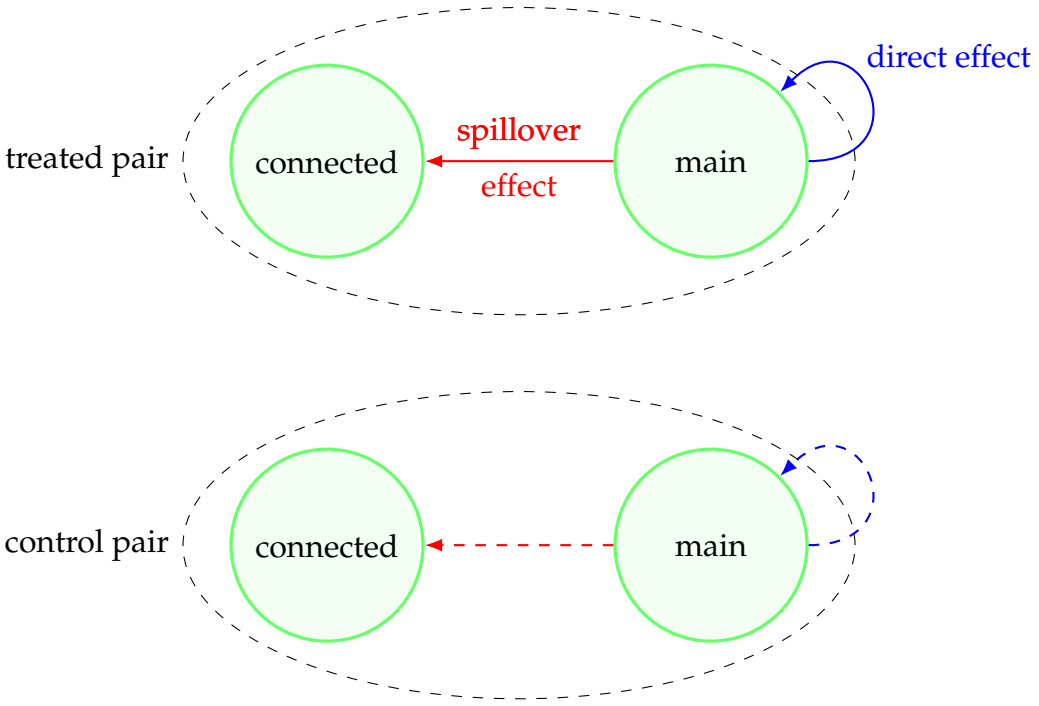
We identify the direct and spillover effects using the variation visualized in Figure 1. The information on GDP forecasts is given to the main firm of the treated pair. We compare the responses given by the main (connected) firm in the treated pair to the main (connected) firm in the control pair to identify the direct (spillover) effects of the treatment.[5] Identification follows from the random assignment of treatment to pairs, if one assumes no interference between pairs—i.e., no effect of treatment between pairs.[6] However, violation of this assumption would likely only attenuate our treatment effects under the reasonable assumption that spillover effects between pairs are of the same sign as, and smaller than, spillovers within pairs. Nonetheless, we attempted to minimize these control contamination concerns by ensuring the primary supplier of the supplier in one pair is not a firm in any other sampled pair.

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

[5]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.

[6]This is a common assumption employed in the literature (Baird et al., 2018), that helps to avoid the many complexities inherent in settings of network interference (Aronow and Samii, 2017; Choi, 2017; Liu and Hudgens, 2014).

Figure 1: Research Design Visualization



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 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 within the pair), and supply chain information (expenditure/sales share and pricing contracts within the pair). 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. Furthermore, not all participating firms responded to each question in the survey, this is reflected in the number of observations varying across columns in the tables presented in Sections 3 and 4.

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:

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

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.

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 is along the 45-degree line in Figure 2, indicating no systematic change in the control firms' beliefs before or after treatment.

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.

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 the 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 of smaller magnitude. This aligns with the results reported by Kumar et al. (2023) and

Coibion et al. (2024), where firms and households, respectively, update their first moment expectations when receiving information about the second moment (and vice versa). 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.

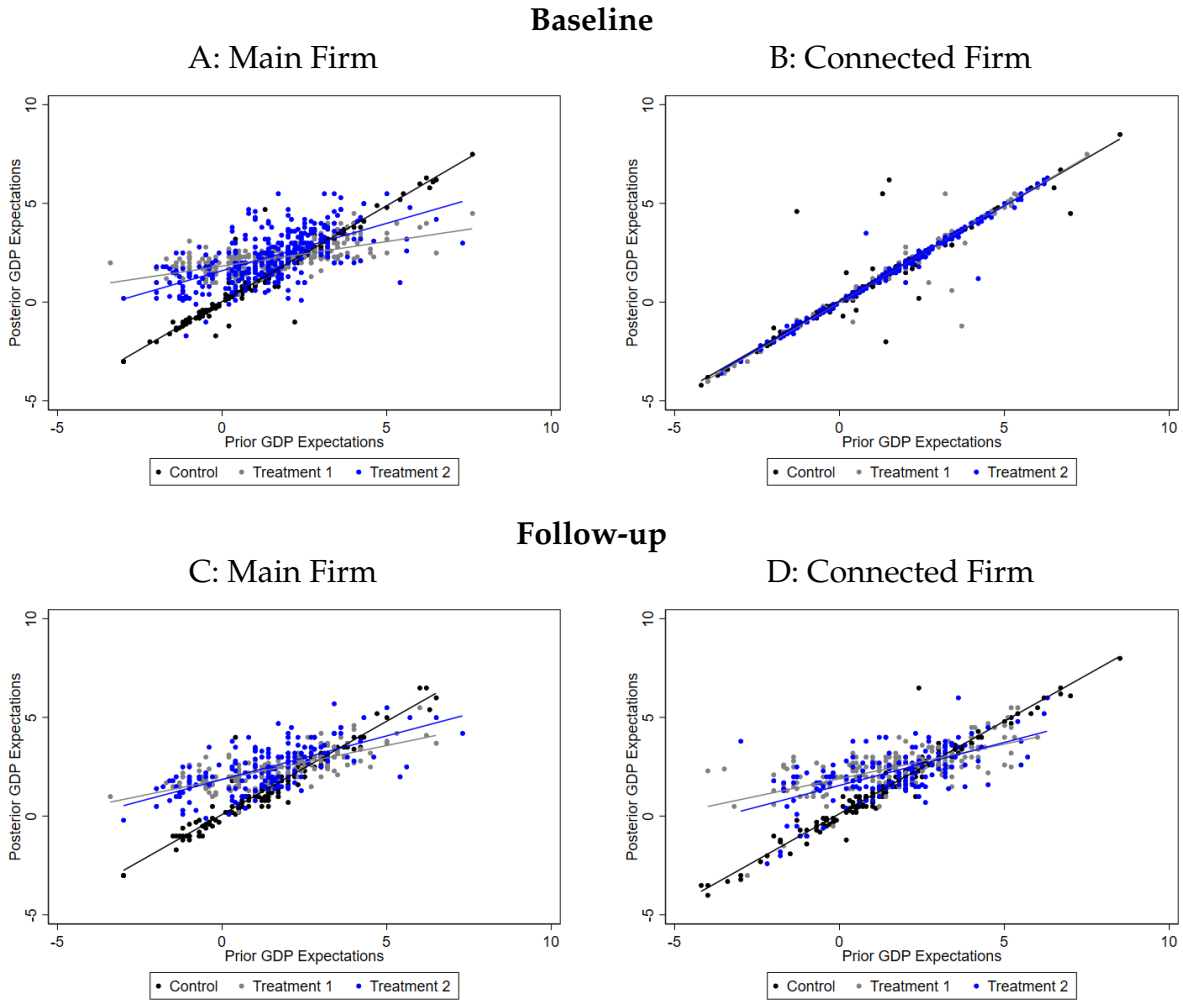
The treatment effect on the connected firm — the spillover effect — in the baseline period (Column 2) from either treatment is insignificantly different from zero. Correspondingly, we see no rotation of the distribution in Panel B of Figure 2. As expected, this suggests information has not yet been diffused 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.

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). The highly persistent impact of treatment is consistent with findings in the literature: Coibion et al. (2021) and Georgarakos et al. (2024), for firms and households respectively, also report effects on beliefs after three months with a magnitude equal to that at baseline. 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 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 diffused from the main firm to the connected firm—i.e., along the supply chain network. The comparable magnitude of the spillover and direct effects furthermore suggests that interactions between firms in the supply chain are important in formation of their macroeconomic beliefs.

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

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).

mean transmitted through the input-output network but also information about uncertainty. These results remain robust when we restrict the sample to firms that

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.

participated in both the baseline and follow-up, as shown in Table A-4.

We examine the heterogeneity of the treatment effects with respect to firm characteristics (size, market share, age, and sector) in Table A-5 (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).[7] 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.

[7] No direct effect on wages is consistent with results in the literature in our setting (Kumar et al., 2023).

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-5 (b). We detect no systematic variation across these dimensions.

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.

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 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 et al. (2022, 2023) and Kumar et al. (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.[8] 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.

[8]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-7 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.

Conversely, higher uncertainty reduces their prices, investment, and employment decisions, related to the contractionary effect of higher uncertainty (Baker et al., 2024). The estimated impact of uncertainty is particularly robust. Moreover, the magnitudes are very similar between main and connected firms.

Summarizing, we find that changes in expectations (both first and second moments) significantly affect firms' decisions. The direct effects confirm findings in the literature (such as in Kumar et al. 2023), while the spillover effects are novel.

4 Evidence for 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.

The results are shown in Table 5. The mean (uncertainty) posterior of the con-

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.

nected firm is shown in Column 1 (3). 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. This mechanism is important for actions too: in Online Appendix Table A-8, we re-run regression (4) but with the actions of the connected firms as the dependent variables, and see the

effects similarly load onto the main firm's posterior.

In Columns 2 and 4, we repeat the analysis, but now 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.[9]

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 they communicated about GDP with the other firm in their 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.

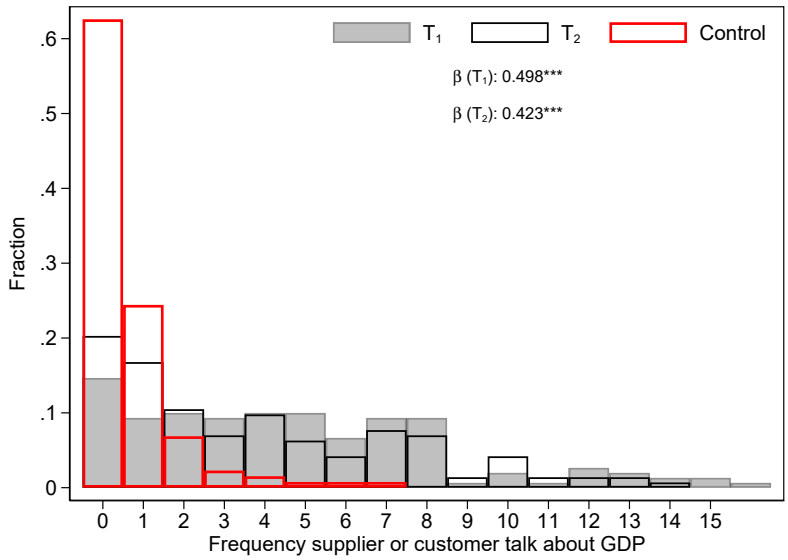
The treatment effect on communication is very strong, with the distribution shifted right under treatment. To give a benchmark, in the control group, 65% of firms report they did not communicate about GDP at all. This is reduced to only 15% (23%) under mean (uncertainty) treatment, and the reduction is statistically significant. See Table A-9 column (1) for the regression.[10]

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

[9] We see analogous results with actions as the dependent variable, as presented in Table A-8. This has potentially important implications for structural estimation, for instance of the Philips Curve slope. If one restricts the sample to main firms being the customer, so that the price change of the connected firm (instrumented by treatment) can be interpreted as a cost shock, one would overestimate the effect of the cost shock by nearly three times if one does not account for communication (the coefficient on $Action^{main}$ in columns 2 vs 1 of Table A-10).

[10] Table A-9 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.

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 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, 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-6 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.

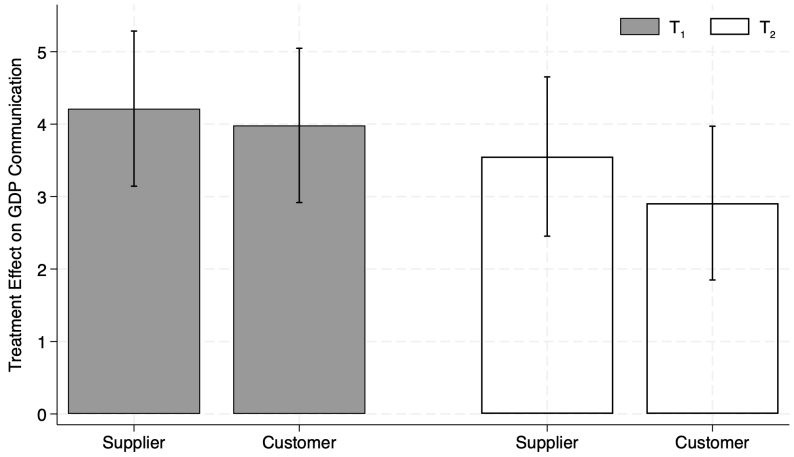
Given this symmetry, for communication to instead be the mechanism it must be that communication between firms is symmetric upstream vs downstream. Figure 4 shows that this is indeed the case. For either treatment, the number of times the main firm reports communicating about GDP (relative to control) is not statistically different whether it is a supplier or a customer.[11] Thus, communication as the underlying mechanism is consistent with the results.

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 optimistic 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

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

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.

results suggest that firms are more collaborative than deceptive.

5 Macroeconomic Implications

Our empirical analysis shows that inter-firm communication plays an important role in explaining the spillover effects of expectations in the supply chain. The purpose of this section is to analyze the implications of communication for the transmission of output growth expectations to firm-level and aggregate inflation. To this end, we embed communication in an otherwise standard New Keynesian pricing problem in a production network.

5.1 Model

Setup. We consider the log-linearized sector-level Phillips curve derived in Rubbo (2023) and assume each of the N sectors is represented by a firm.[12] The price vector

[12]We think of firms as producing many varieties and adjusting prices for only a share of them at a given time. Moreover, our setting abstracts from productivity shocks, implying that all of our results

$\boldsymbol{p}_t$ containing each firm's average price is

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

where y_t is output growth, a measure of slack in the economy; $\widetilde{\mathbb{E}}_t$ 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 among firms, labor and consumption shares, and price flexibility; $\boldsymbol{\kappa}$ is the vector of Phillips curve slopes; and $\Delta = (I + \beta\Omega)^{-1}$ (see Appendix B.1 for details).

Output growth is exogenously given and is driven by a deterministic sequence μ_t and a mean-zero iid shock ε_{t+1}, $y_{t+1} = \mu_t + \varepsilon_{t+1}$.[13] The long-run behavior of μ_t converges to that of an iid normal stochastic process with mean zero and that is independent of ε_t. Firms have imperfect information about the current realization of the deterministic component 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. To solve the model, therefore, we have to discipline firms' expectations about future growth. Before spelling out details, we clarify our timing assumption within a period: any firm j starts off with prior expectations about output growth, $\widetilde{\mathbb{E}}_{jt}^{prior} y_{t+1} = e_{jt}$; some firms receive an information treatment about μ_t prompting an update in their expectations; firms communicate their expectations with each other; and finally make pricing decisions.

As in the experiment, a firm j receives a signal $s_{jt} = \mu_t + \epsilon_{jt}$, with noise $\epsilon_{jt} \sim N(0, \sigma^2_{\epsilon_j})$, containing information about future output growth, prompting the firm to update its expectations about future output growth to

$$\widetilde{\mathbb{E}}_{jt}^{post} y_{t+1} = g_j s_{jt} + (1 - g_j) \widetilde{\mathbb{E}}_{jt}^{prior} y_{t+1}, \tag{6}$$

where $g_j = \frac{\sigma^2_\mu}{\sigma^2_\mu + \sigma^2_{\epsilon_j}}$ denotes the Kalman gain from the information treatment.

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).

[13] Making an explicit assumption about the law of motion for output growth is useful to derive the analytical solution of the model and analyze the role of communication in Appendix B.2.

Communication. Motivated by our empirical evidence, firms communicate their future output growth expectations with other firms on their supply chain network according to an exogenous communication matrix $C = [c_{ij}]$ that firms take as given.[14] $c_{ij} \in [0, 1]$ quantifies the intensity with which firm j communicates its expectations about future output growth to firm i, and $\sum_{j=1}^{N} c_{ij} = 1$.

While our empirical analysis provides strong evidence in support of communication between a firm and its main supplier, it does not provide direct evidence on how firms aggregate information from the whole set of firms they communicate with, or on the weight they assign to each connection (i.e. the structure of C). For the first, we therefore impose a standard social learning process based on the model of DeGroot (1974) whereby the *final* output growth expectations of any firm i are a weighted average—with weights given by C—of the posterior expectations of all firms:[15]

$$\widetilde{\mathbb{E}}_{it} y_{t+1} = \sum_{j=1}^{N} c_{ij} \widetilde{\mathbb{E}}_{jt}^{post} y_{t+1}. \tag{7}$$

For the second, for some of the results we will appeal to two special cases for C: 1) *no communication*, given by $C = I$, and 2) *uniform communication*, where firms assign equal weight to all other firms, given by $C = \mathbf{1}_{N \times N}/N$.[16] These polar cases, although restrictive, provide natural benchmarks for the potential macroeconomic effects of communication.

Equilibrium inflation. The vector of equilibrium inflation rates across firms, $\boldsymbol{\pi}_t = \boldsymbol{p}_t - \boldsymbol{p}_{t-1}$, is given by

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

[15] The DeGroot model of social learning has extensive use in economics and has emerged as a credible model of boundedly rational information aggregation in network settings (Golub and Jackson, 2010; Banerjee et al., 2021).

[16] In Appendix B.4, we consider another communication matrix, $C = \Omega$, so that the intensity of communication equals the sensitivity of the firms' prices to the vector of past prices and future expected price changes.

$$\boldsymbol{\pi}_t = \beta MCG\boldsymbol{s}_t + \beta MC(I-G)\boldsymbol{e}_t + M_y\mathbf{1}y_t + (M_p - I)\boldsymbol{p}_{t-1}, \tag{8}$$

where G is a diagonal matrix containing Kalman gains, and $M_p, M_y\mathbf{1}, M$ are matrices with all positive elements, described in Appendix B.1. Aggregate inflation is given by $\bar{\pi}_t = \boldsymbol{\psi}'\boldsymbol{\pi}_t$, where ψ_j is the share of firm j in household consumption. The matrix M being positive implies that, consistent with our empirical evidence, a one-time positive signal about future output growth raises individual—and aggregate—inflation on impact.[17]

Parameterization. To provide some quantitative insight, we calibrate a fifty firm ($N = 50$) version of the model. We match key characteristics of the firms in our sample (such as price flexibility and labor cost shares) and set the other parameters to standard values (see Appendix B.1 for details).

5.2 Implications

Firm-Level Inflation Dispersion and Persistence. Uniform communication implies that the inflation response is independent of which firm receives the information treatment (Corollary 1 in the Appendix). Intuitively, all firms effectively receive the same signal as the treated firm communicates with all other firms. This means, for instance, that a firm's inflation rate responds the same whether its supplier or customer firm are treated, consistent with our empirical evidence in Table 6.

Uniform communication does not imply, however, that given an information shock to some firm, the resulting variation in inflation rates across all firms is less compared to no communication. The effect on dispersion depends on the firm-level Phillips curve slopes κ_j: we prove in the appendix (Corollary 2) that uniform communication does imply less dispersion under homogeneous κ_j. Intuitively, as some firm inflation rates may respond much more strongly to information than others, and as communication effectively spreads the treatment around, the resulting

[17] Appendix B.5 derives a version of the model with uncertainty about future output growth and shows that, yet again consistent with our empirical results, higher uncertainty causes firms to lower prices leading thus to a decline of inflation on impact.

changes in inflation rates can be much more varied than if treatment is only directly incident on one firm (i.e. no communication). We may expect, therefore, communication to reduce dispersion if heterogeneity in κ_j is sufficiently limited: under our calibration of the model, we always see a reduction in dispersion (see Figure 5.A). This is also consistent with suggestive evidence from our experiment, where price dispersion within the firm-pair is less for firms that reported they communicated about GDP.[18]

For any communication pattern C, the persistence in inflation rates is determined by the level of dispersion. This is because the last term in equation (8), $(M_p - I)\boldsymbol{p}_{t-1}$, is the only source of persistence, and this is zero if prices in $t-1$ are equal across all firms. This follows because M_p is a row stochastic matrix, which we prove in the appendix. This builds on a standard property of New Keynesian frameworks: in response to a one-time, iid shock, inflation will continue to deviate from the steady state until all prices converge to the new aggregate price level.

Aggregate Inflation. For analytic tractability, consider the change in the long run aggregate price level. Without communication, the effect from a shock to firm j, s_j, is given by

$$\Theta_j \equiv a\lambda_j\kappa_j g_j \frac{1-\phi_j}{\phi_j} \tag{9}$$

where ϕ_j is firm j's nominal price flexibility and $a \equiv \frac{\beta}{\sum_i \lambda_i \frac{1-\phi_i}{\phi_i}} > 0$ (see Proposition 2 for details).[19] Θ_j depends on firm j's position in the supply chain through its Domar weight, λ_j, and Phillips curve slope κ_j, paralleling the recent production network literature on the aggregate effects of firm-level shocks. λ_j is large essentially if firm j is upstream, as price changes cascade downstream (Carvalho and Tahbaz-Salehi, 2019). κ_j is large if the firms upstream of j have flexible prices, as then j expects greater increases in input costs due to future output growth (La'O

[18] Specifically, we estimate the connected firm's price change associated with a 1 percentage point exogenous rise in the main firm's price. We find that when there is communication, the estimated price relationship between the treated and connected firm approaches unity, whereas absent communication, the point estimate of the price relationship is always less then unity (see Table A-11 in the Appendix).

[19] As in Rubbo (2023), $\phi_j = \frac{\hat{\phi}_j(1-\beta(1-\hat{\phi}_j))}{1-\beta\hat{\phi}_j(1-\hat{\phi}_j)}$, where $\hat{\phi}_j$ is the primitive Calvo parameter for firm j.

and Tahbaz-Salehi, 2022; Pastén et al., 2024). With communication, the impact on the long run aggregate price level is $\sum_{i=1}^{N} \Theta_i \frac{g_j}{g_i} c_{ij}$. The original dependence on j's position in the production network through Θ_j is now weakened, as it also depends on the Θ_i of the firms that j communicates with. For instance, downstream firms can cause large price cascades—counter to that implied by their Domar weight—if they communicate with upstream firms.[20] Our experimental results point to this possibility given the evidence on spillover effects flowing symmetrically up and downstream (Section 4).

Moreover, despite communication propagating the shock to more firms, it does not necessarily amplify its impact on aggregate inflation compared to no communication. Under DeGroot learning, firms down-weight their own information relative to no communication, as now they put weight on other firms' information: c_{jj} in equation (7) is < 1 when firms communicate, while $= 1$ under no communication. This channel causes an offsetting, attenuating effect of communication. Communication amplifies the effect of s_j on the long-run aggregate price level relative to no communication if and only if (see Corollary 3)

$$\sum_{i \neq j} \frac{\Theta_i}{g_i} c_{ij} > \frac{\Theta_j}{g_j} \left(1 - c_{jj}\right). \tag{10}$$

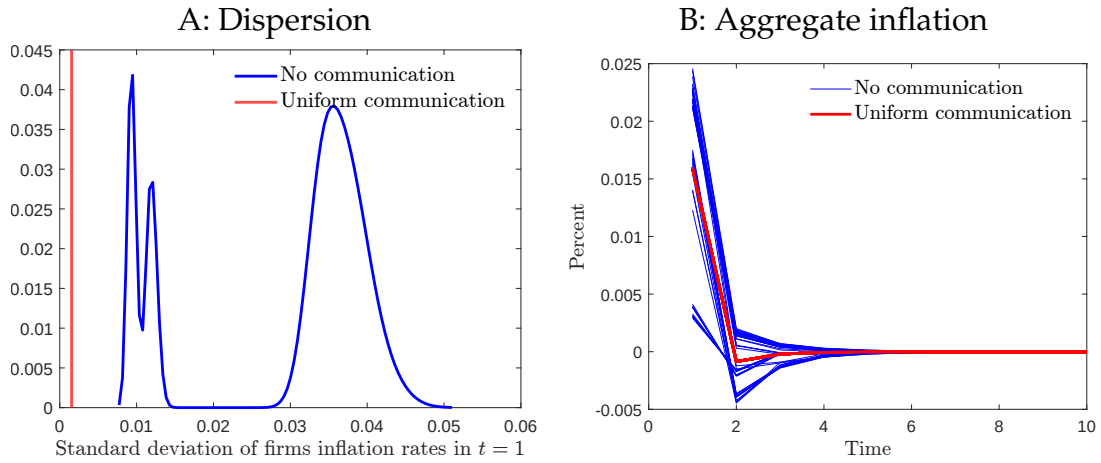
The left-hand side is the amplifying effect due to communication propagating the shock to other firms $i \neq j$, while the right-hand side is the attenuating effect due to a firm down-weighting its own information.

Communication, therefore, can have non-trivial aggregate implications. We explore this in the context of uniform communication in Figure 5.B. The blue lines show the effect on aggregate inflation under no communication, with each line corresponding to a different firm shocked. The red line shows the impact under uniform communication, which is the same for all firms (recall the effect on inflation is independent of which firm is treated). Under uniform communication, the dependence on the firm's Domar weight and Phillips curve slope is completely severed,

[20] Figure A-6 in the Appendix visualizes the role of communication for the response of aggregate inflation and long-run price level when a supplier versus a customer firm receives the treatment, based on simulations of a three-firm production network.

as the effect on aggregate inflation is equal across all firms. Moreover, relative to no communication, the effect on aggregate inflation is amplified when the treatment is provided to some firms, while attenuated when provided to others, consistent with the two competing channels of communication described above.

Figure 5: Effects of Communication for Inflation



Note: Panel A plots the distribution of the standard deviation of firms' inflation rates in period $t = 1$ when there is communication (red) versus not (blue). Panel B shows the response of aggregate inflation with uniform communication (red) and without communication (blue) across simulations. Each point in the distributions in both panels corresponds to a different firm receiving the signal s_j.

Communication re-configuring the transmission of macroeconomic expectations, offers new insights for policy communication. Absent inter-firm communication, policymakers can maximize the impact of their communication by targeting firms with high Θ_j, whose expectations are most influential for prices and inflation. When firms communicate with each other, the response of the long-run price level to a treatment given to firm j is $\sum_{i=1}^{N} \frac{\Theta_i g_j}{g_i} c_{ij}$. Hence, policy can alternatively focus on firms that communicate a lot with other firms in their supply chain networks. This is most apparent in the extreme case when all firms share the same Θ_j and g_j: policy makers' communication efforts would yield the highest impact if focused on firms that have the highest $\sum_{i=1}^{N} c_{ij}$. That is, if firm j has many firms i it communicates with (i.e., $c_{ij} > 0$), or communicates alot with a more limited number of firms (i.e., high c_{ij} for some firms i).

6 Conclusion

Using a randomized controlled trial of firm-firm pairs, we examine the role that supply chain networks play for the expectation formation process of firms. We exploit exogenous variation from a GDP information treatment and estimate spillover effects between firms; this presents a new direction for the growing macroeconomic survey literature, which has been confined to direct effects. We detect spillover effects as large as the direct effects, both on their expectations and actions—pricing, investment, and employment. These findings suggest that learning along the supply chain is an important factor in the formation of a firm's macroeconomic expectations.

We provide evidence that communication is a key mechanism underlying how firms learn from one another, as opposed to firms inferring about the aggregate state from, for example, prices of other firms in their supply chain. This is consequential because we find that information spreads symmetrically up and down the supply chain under communication, whereas shock propagation via prices is known to flow predominantly downstream. We introduce communication into a New Keynesian production network model to provide insight on its macroeconomic implications. The analysis complements our experimental evidence, suggesting communication can fundamentally alter the propagation of shocks in supply chains.

Our results yield several policy implications. First, central banks, in their effort to anchor expectations, may want to exploit firm communication networks. Rather than attempting to disseminate their inflation target—for instance—to all firms, they could instead leverage firms that are appropriately central in the communication network, as they will communicate this information with many other firms on their behalf. Second, our analysis suggests that accounting for firms' expectations is even more important when estimating policy-relevant parameters such as the Phillips curve slope. This is because communication opens up a new structural channel in the price-setting behavior of firms, which needs to be controlled for to ensure valid identification.

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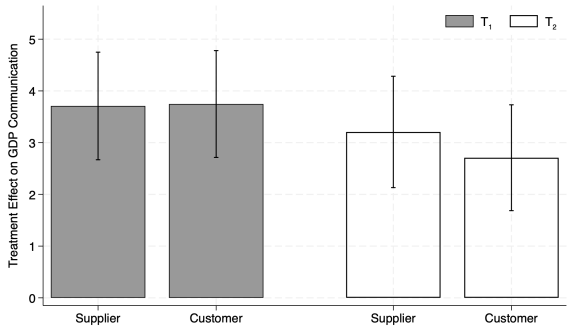
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Supplemental Appendix

A Additional Figures and Tables

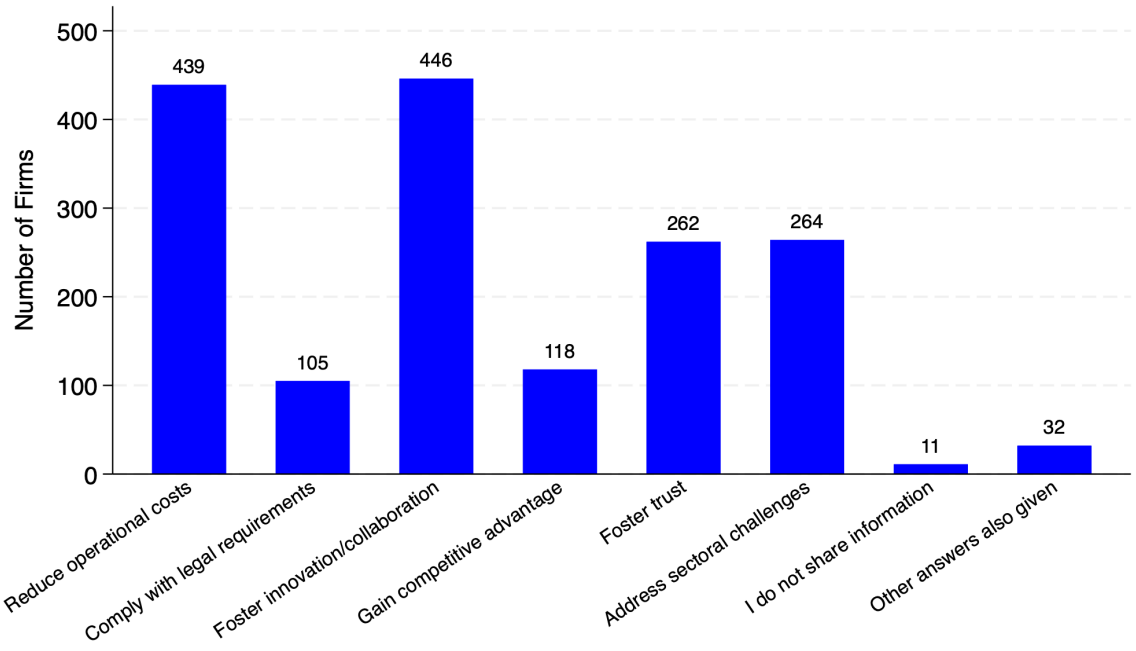
A.1 Figures

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-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-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-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: Treatment Effect on GDP Expectations and Uncertainty in Baseline and Follow-up: *Restricted sample where firms are in both waves*

	Mean		Uncertainty	
	(1)	(2)	(3)	(4)
Prior	0.970***	0.951***	0.941***	1.007***
	(0.0105)	(0.0282)	(0.0367)	(0.0128)
T_1	1.871***	-0.105	1.620***	0.0533
	(0.0608)	(0.0740)	(0.368)	(0.0800)
T_2	1.775***	-0.0968	1.252***	0.120
	(0.102)	(0.0735)	(0.280)	(0.102)
$T_1 \times$ *Prior*	-0.731***	0.0432	-0.789***	-0.0109
	(0.0271)	(0.0285)	(0.0569)	(0.0131)
$T_2 \times$ *Prior*	-0.527***	0.0290	-0.737***	-0.0302
	(0.0546)	(0.0285)	(0.0500)	(0.0183)
Observations	515	514	519	519
R-squared	0.723	0.965	0.805	0.970
Period Posterior	Baseline	Baseline	Basline	Baseline
Type of firm	Main	Connected	Main	Connected

Note: The table reports results of regression 1, where the outcome variable in columns (1) and (2) is $posterior^{mean}$, which is the average GDP forecast of firm i after the treatment; in columns (3) and (4) is $posterior^{uncertainty}$, which 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. $Prior$ a prior before the treatment and it is either $prior^{mean}$ – the average GDP forecast in columns (1) and (2); or $Prior^{uncertainty}$ – the uncertainty forecast in columns (3) and (4). 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 (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.

Table A-5: 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-6: 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-7: 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-8: 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-9: 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-10: 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 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), $\Phi = diag(\phi_1, \phi_2, ..., \phi_N)$ where $\phi_i = \frac{\hat{\phi}_i(1-\beta(1-\hat{\phi}_i))}{1-\beta\hat{\phi}_i(1-\hat{\phi}_i)}$ with $\hat{\phi}_i$ being the primitive 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.

Parameterization of the model. We consider a network of $N = 50$ firms and use data from the first wave to parameterize the model. Since the price vector $\boldsymbol{p}_t$ embeds the average price of each firm, we compute the distribution of the Calvo probabilities $\hat{\phi}$ by taking the average frequency of price adjustment across firms within a subsector and type of firm (supplier vs customer).[21] Similarly, we compute the distribution of the labor shares α by computing the average labor cost share across firms within a sector. We then randomly draw $N = 50$ times from the distribution of ϕ and α. Next, we randomly draw from a uniform distribution (between 0 and 1) to fill in the IO matrix such that $\sum_{j=1}^{N} IO_{ij} + \alpha_j = 1$ for any $i \in \{1, 2, ..., N\}$. 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).[22] Finally, we

[21] 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%.

[22] 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 $\hat{\theta}/\hat{\beta}$.

set the discount factor β equal to 0.9975 and $\varphi = 3$ as in Rubbo (2023), and allocate equal consumption shares to firms $\boldsymbol{\psi} = \mathbf{1}/N$.

B.2 Analytical 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. The vector of all firms' expectations about future growth can be written as

$$\widetilde{\mathbb{E}}_t \boldsymbol{y}_{t+1} = C\left(G\boldsymbol{s}_t + (I - G)\boldsymbol{e}_t\right) \tag{B.3}$$

where $\boldsymbol{y}_t = \mathbf{1}y_t$, G is a diagonal matrix containing the Kalman gains, $\boldsymbol{s}_t$ is the vector of signals, and $\boldsymbol{e}_t$ is the vector of prior output growth expectations. Proposition 1 provides the equilibrium price vector and shows that an information treatment about higher future output growth (higher s_{jt}) leads to higher prices, as documented by our empirical results in Table 4.

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

$$\boldsymbol{p}_t = \beta MCG\boldsymbol{s}_t + \beta MC(I - G)\boldsymbol{e}_t + M_y\boldsymbol{y}_t + M_p\boldsymbol{p}_{t-1},$$

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

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

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

COROLLARY 2. *Following a treatment to firm j, there will always be dispersion in the initial firm price responses absent communication; under uniform communication, there will be dispersion in the initial firm price responses only to the extent that the Phillips curve slopes, $\boldsymbol{\kappa}$, are heterogeneous. If firms have the same price flexibility and labor share, firms share the same Phillips curve slopes, in which case uniform communication implies no price dispersion.*

Aggregate price level and inflation. A one-time treatment about future output growth 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 average 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*

$$\lim_{h\to\infty} P_{t+h} = \lim_{t\to\infty} \boldsymbol{\psi}' \boldsymbol{p}_{t+h} = \sum_i \frac{\Theta_i g_j}{g_i} c_{ij},$$

where Θ_i is the response of the long-run price level to s_{it} absent communication. Θ_i is the i^{th} element of $\boldsymbol{\Theta} = \frac{\beta \boldsymbol{\lambda}(I-\Phi)\Phi^{-1} diag(\boldsymbol{\kappa}) G}{\sum_i \lambda_i \frac{1-\phi_i}{\phi_i}}$, where $\boldsymbol{\lambda} = \boldsymbol{\psi}'(I - IO)^{-1}$ is the vector of Domar weights.

$\boldsymbol{\Theta}$ connects nicely with upstream flexibility, defined in La'O and Tahbaz-Salehi (2022), through the Phillips curve slope. Specifically upstream flexibility is given by $\boldsymbol{\rho} = (I - IO\Phi)^{-1}\boldsymbol{\alpha}$. One can then show that $(I - \Phi)\Phi^{-1}diag(\boldsymbol{\kappa}) \propto (I - \Phi)diag(\boldsymbol{\rho})$, implying that the response of the long-run price level to a treatment received by firm j can be alternatively expressed as

$$\Theta_j = b\lambda_j g_j \rho_j (1 - \phi_j), \tag{B.4}$$

for constant $b \equiv \frac{\beta\varphi}{(1-\boldsymbol{\psi}\Phi(I-IO\Phi)^{-1}\boldsymbol{\alpha})\sum_i \lambda_i \frac{1-\phi_i}{\phi_i}} > 0$.

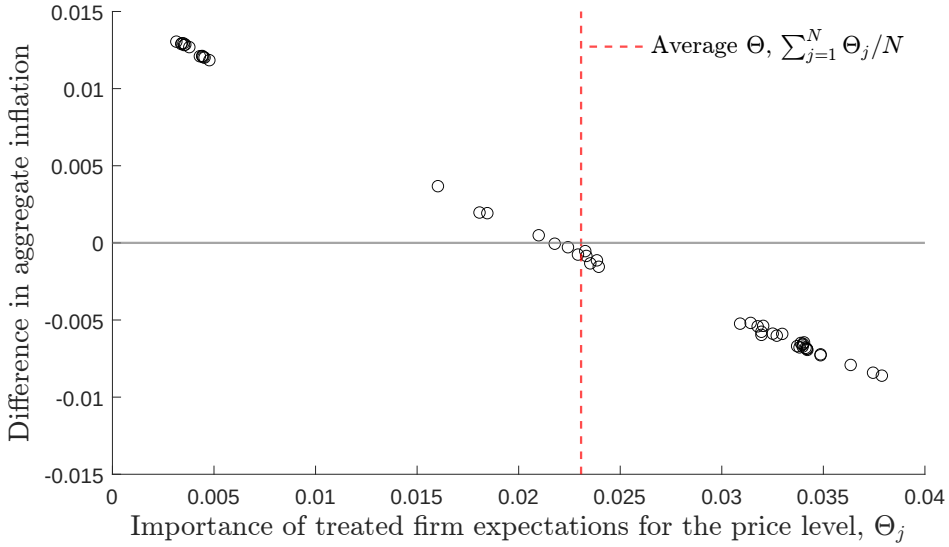
Corollary 3 formalizes the condition for which communication amplifies the response of the long-run aggregate price level to an information treatment received by firm j: relative to no communication, communication is more likely to propagate the effects of expectations on the long-run price level when the treatment originates from a firm whose expectations are not particularly important for the long-run price level but who communicates a lot with firms whose expectations are highly important (i.e., firm j communicates with firms i with high Θ_i). This condition turns out to be a good predictor for when communication amplifies the response of aggregate inflation on impact: relying on data from the model simulation, Figure A-3 shows that when uniform communication amplifies the response of the long-run price level it generally also propagates the impact response of aggregate inflation.

COROLLARY 3. *Relative to no communication, communication $C = [c_{ij}]$ amplifies the response of the long-run aggregate price to a treatment received by firm j if and only if*

$$\sum_{i=1}^{N} \frac{\Theta_i}{g_i} c_{ij} - \frac{\Theta_j}{g_j} > 0. \tag{B.5}$$

The expectations of firms with a higher Θ have a larger impact on the long-run price level absent communication.

Figure A-3: Aggregate Inflation With vs Without Communication by the Importance of Treated Firm's Expectations



Note: The figure shows a scatter plot between the importance of the treated firm's expectations for the long-run price level under no communication in the x-axis and the difference between the impact response of aggregate inflation under uniform communication versus no communication. Data comes from the simulation of the model with $N = 50$ firms.

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

$$\bar{\pi}_t = \boldsymbol{\psi}' \left[\beta MCG \boldsymbol{s}_t + M_y \boldsymbol{y}_t + (M_p - I)\boldsymbol{p}_{t-1} \right]. \tag{B.6}$$

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. [23]

[23] From Proposition 1 and $\sum_j (M_p)_{ij} = 1 \; \forall i$, it follows that if the initial price response is homogeneous, that is, $\boldsymbol{p}_t \propto \mathbf{1}$, 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 in period t will lead to a one-time change in inflation in period t, after which inflation reverts to its steady state.

B.3 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 (B.3) in the case of expectations responses; Corollary 3 follows directly from Proposition 2.

B.3.1 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:

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

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

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

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

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

From here, it follows that

$$\begin{aligned} M_p - \beta\Delta\Omega M_p^2 &= \Delta\Omega \\ M_y &= (I - \beta\Delta\Omega M_p)^{-1}\Delta K \\ M_e &= -\beta(I - \beta\Delta\Omega M_p)^{-1}\Delta\Omega M_y C(I-G) \\ M_s &= \beta(I - \beta\Delta\Omega M_p)^{-1}\Delta\Omega M_y CG \end{aligned} \tag{B.7}$$

It is straightforward to see from the first equation above that $M_s = \beta M_p M_y CG$ and $M_e = -\beta M_p M_y C(I-G)$. 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: $M_p^2 - (\Omega^{-1}/\beta + I)\, M_p + I/\beta = \mathbf{0}_N$. 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.3.2 Proof of Corollary 2

The response of the price vector is given by $\frac{\partial \boldsymbol{p}_t}{\partial s_{jt}} = \beta g M_p^2 \Omega^{-1} diag(\boldsymbol{\kappa}) C_{:j}$. 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 uniform communication is given by

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

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 $\beta g \kappa$.

In the special case where all firms share the same ϕ and labor share α, one can write the expression for $\boldsymbol{\kappa}$ as

$$\boldsymbol{\kappa} = \alpha\varphi \frac{\phi(I - \phi IO)^{-1}\mathbf{1}}{1 - \phi\alpha\boldsymbol{\psi}(I - \phi IO)^{-1}\mathbf{1}}.$$

The sum of the elements in each row of $(I - \phi IO)$ is $1 - \phi(1-\alpha)$, hence one can write $(I - \phi IO) = (1 - \phi(1-\alpha))\frac{(I-\phi IO)}{1-\phi(1-\alpha)}$ where $\frac{(I-\phi IO)}{1-\phi(1-\alpha)}$ is a stochastic matrix. Hence,

$$\boldsymbol{\kappa} = \frac{\alpha\phi\varphi}{1 - \phi(1-\alpha)} \frac{\left(\frac{I-\phi IO}{1-\phi(1-\alpha)}\right)^{-1}\mathbf{1}}{1 - \phi\alpha\boldsymbol{\psi}(I - \phi IO)^{-1}\mathbf{1}} = \frac{\alpha\phi\varphi}{(1 - \phi(1-\alpha))(1 - \phi\alpha\boldsymbol{\psi}(I - \phi IO)^{-1}\mathbf{1})}\mathbf{1},$$

implying that all firms share the same Phillips curve slope κ.

B.3.3 Proof of Proposition 2

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

$$\lim_{h\to\infty} \boldsymbol{p}_{t+h} = \beta g_j \lim_{h\to\infty} M_p^{h+1} M_y C_{:,j} = \beta g_j \lim_{h\to\infty} M_p^{h+2} \Omega^{-1} diag(\boldsymbol{\kappa}) C_{:,j}, \tag{B.8}$$

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

$$\lim_{h\to\infty} M_p^{h+2}\Omega^{-1} = Q \begin{bmatrix} 1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} Q^{-1} = \begin{bmatrix} Q_{11}Q_{1:}^{-1} \\ Q_{21}Q_{1:}^{-1} \\ ... \\ Q_{N1}Q_{1:}^{-1} \end{bmatrix} = \begin{bmatrix} Q_{1:}^{-1} \\ Q_{1:}^{-1} \\ ... \\ Q_{1:}^{-1} \end{bmatrix},$$

where the last equality follows from the fact that the eigenvector of M_p associated with the unit eigenvalue is $Q_{:1} = \mathbf{1}$. $Q_{1:}^{-1}$ is the first column of the inverse of Q and it 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 the eigenvector that is associated with the unit eigenvalue of Ω' is $Q_{1:}^{-1} \propto \boldsymbol{\lambda}(I - \Phi)\Phi^{-1}$. Note that since M_p^2 and Ω^{-1} are stochastic matrices and $M_p^2\Omega^{-1}$ contains positive elements only; therefore, $\lim_{h\to\infty} M_p^{h+2}\Omega^{-1}$ is also a stochastic matrix and all its elements are positive. Hence,

$$\lim_{h\to\infty} M_p^{h+2}\Omega^{-1} = \frac{1}{\sum_i^N \lambda_i \frac{1-\phi_i}{\phi_i}} \begin{bmatrix} \boldsymbol{\lambda}(I-\Phi)\Phi^{-1} \\ \boldsymbol{\lambda}(I-\Phi)\Phi^{-1} \\ \dots \\ \boldsymbol{\lambda}(I-\Phi)\Phi^{-1} \end{bmatrix},$$

where the division by $\sum_i^N \lambda_i \frac{1-\phi_i}{\phi_i}$ ensures that $\lim_{h\to\infty} M_p^{h+2}\Omega^{-1}$ is a stochastic matrix. From here it follows that $\lim_{h\to\infty} P_{t+h} = \frac{\beta g_j \boldsymbol{\lambda}(I-\Phi)\Phi^{-1} diag(\boldsymbol{\kappa}) C_{:j}}{\sum_i \lambda_i \frac{1-\phi_i}{\phi_i}}$.

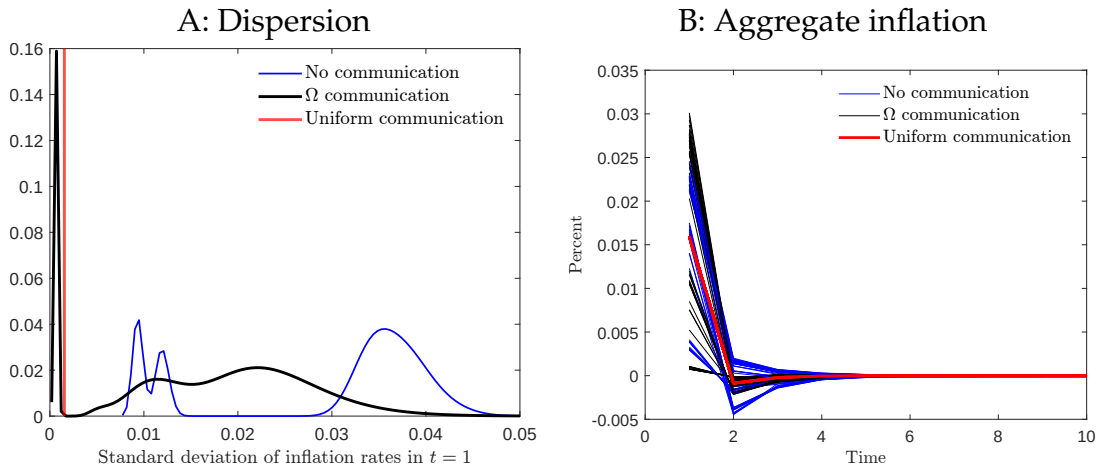
B.4 Additional Quantitative Results

B.4.1 Alternative Communication Matrix

We consider an alternative communication matrix, $C = \Omega$; Ω captures the intensity of communication equals the sensitivity of the firms' price changes to the vector of future expected price changes.[24] Figure A-4 shows that in the case of $C = \Omega$, the price responses are amplified relative to the no communication scenario, but not by as much as they are under uniform 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.

[24] Applying the definition of Δ in (B.2) in equation (B.1) implies that $\boldsymbol{p}_t = \boldsymbol{\kappa} y_t + \beta\Omega\widetilde{\mathbb{E}}_t\left[\boldsymbol{p}_{t+1} - \boldsymbol{p}_t\right] + \Omega\boldsymbol{p}_{t-1}$. Hence, Ω captures the sensitivity of the current price vector to both expected future changes in prices relative to current prices and to past prices.

Figure A-4: Effects of Communication for Inflation



Note: Panel A plots the distribution of the standard deviation of firms' inflation rates in period $t = 1$ when there is communication (red) versus not (blue). Panel B shows the response of aggregate inflation with uniform communication (red) and without communication (blue) across simulations.

B.4.2 Simulation of a Smaller Network

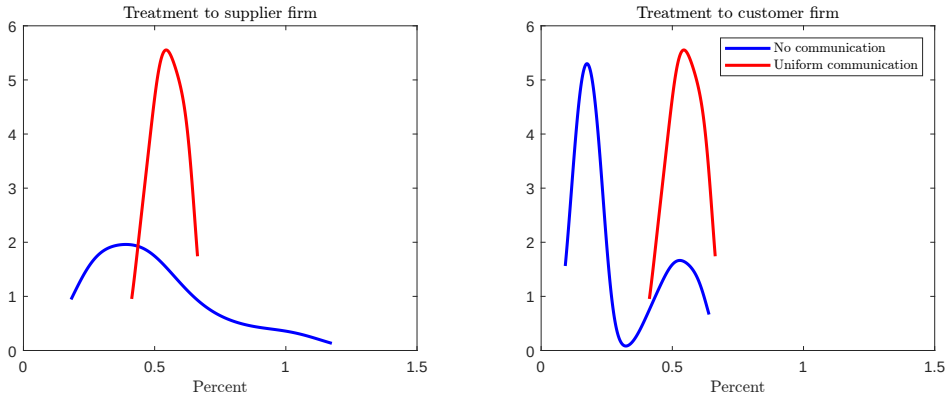
We consider a three-firm model, where one firm is the customer firm (firm 3), one the supplier firm (firm 2), and the other one captures the rest of the network (firm 1). The customer firm purchases its inputs from firms 1 and 2, while the supplier purchases its inputs only from firm 1.[25] We simulate 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, $\iota_{32} \in \{0, 0.1, 0.2, ..., 1 - \alpha_3\}$. We set α_3 equal to 0.39, the average labor share cost reported from the treated 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 0.61 and 0.72, respectively, consistent with the average frequency of price adjustment of all treated

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

supplier and customer firms in our sample, respectively. We set the adjustment probability of firm 1 equal to approximately 0.63 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 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.

Figure A-5 plots the distribution of the initial response of prices to an information treatment about higher future output growth provided to the supplier (left panel) and to the customer (right panel). The red distributions in Figure A-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. 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.

Figure A-5: Distribution of the Impact on Prices after Treatments in Response to Higher Output Growth Expectations



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: uniform communication; in blue: no communication.

Figure A-5 further shows that communication heavily reduces the dispersion of

price changes on impact following a treatment to the supplier or customer. The low price dispersion under uniform communication is consistent with our empirical results: most treated firms report communicating about GDP more than firms in the control group (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 results of this exercise in Table A-11.[26] 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.

Finally, Panels A and B in Figure A-6 plot the evolution of firm prices over time, averaged across simulations, when the supplier 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

[26] Instrumenting the price change of the main firm with interactions between the treatment dummy and the price plan that the firm had, we estimate β_1 and β_2 in the following regression

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

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.

[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.

Table A-11: Price Pass-through from Treated to Connected Firms

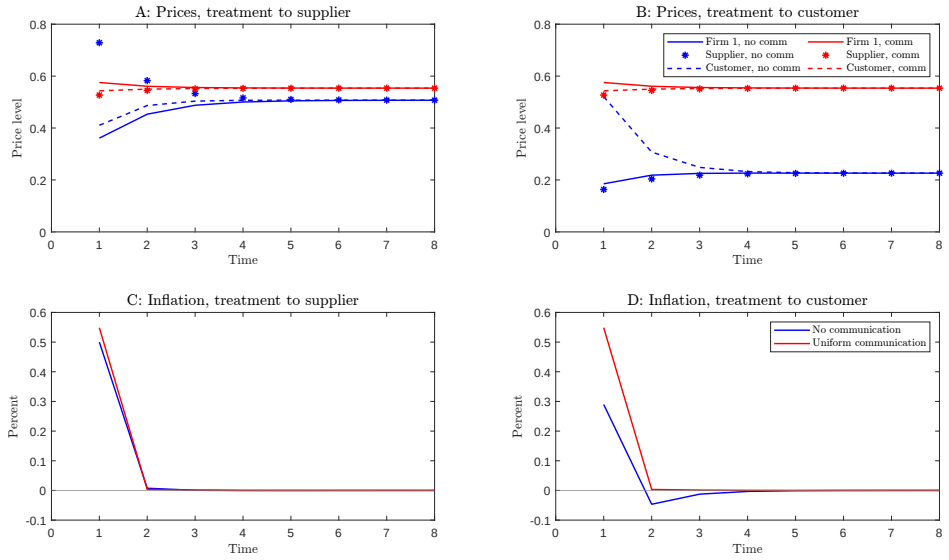
	(1)	(2)	(3)	(4)
$Price^{treated}\|Talk\ GDP$	0.816***		0.810***	
	(0.158)		(0.224)	
$Price^{treated}\|No\ Talk\ GDP$	0.261		0.631***	
	(0.179)		(0.205)	
$Price^{treated}\|Uniform\ Comm$		0.972***		1.028***
		(0.004)		(0.004)
$Price^{treated}\|No\ Comm$		0.317***		0.569***
		(0.005)		(0.010)
Type	Supplier	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	0.874	0.441	0.609

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.

communication case when the treated firm is the customer compared to the supplier. Panels C and D show that communication amplifies the average impact of output growth expectations on inflation, consistent with communication amplifying the initial price response of most firms, relative to no communication, as shown in Figure A-5.[28] However, since there is little price dispersion in the presence of communication, this effect is very short-lived. Our robust finding that the firm where the treatment originates is irrelevant for the response of prices is also evident for inflation dynamics.

[28]The propagative effects of communication have also been emphasized in Angeletos and La'O (2013) in the context of sentiment shocks. However, as we describe in the main text and Appendix B.2, communication does not always amplify the response of prices or inflation to output growth expectations.

Figure A-6: Evolution of Prices and Aggregate Inflation in Response to Higher Output Growth Expectations



Note: Panels A and B plot the evolution of price levels, averaged across simulations, when a treatment of higher 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: uniform communication; in blue: no communication.

B.5 Model with Knightian Uncertainty

Recall the law of motion for output growth, $y_{t+1} = \mu_t + \varepsilon_{t+1}$. Similar to Ilut and Schneider (2014), we assume that firms cannot distinguish the deterministic sequence μ_t from the iid shock ε_{t+1} even if they observe an infinitely large amount of data. Firms face Knightian uncertainty, whereby they cannot assess the probability distribution of outcomes accurately, and are averse to ambiguity arising from not being able to distinguish the deterministic component from the iid component of growth.[29] 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

[29] Ambiguity-aversion is a tractable way for uncertainty to be relevant for decisions despite the fact that we log-linearize the model (Ilut and Schneider (2014)). See Epstein and Wang (1994) for an early application of such uncertainty to asset pricing and Ilut and Schneider (2023) for a recent review.

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

$$y_{t+1} = \mu_{jt} + \varepsilon_{j,t+1}, \qquad \mu_{jt} \in [-a_{jt}, -a_{jt} + 2|a_{jt} + \bar{a}|] \tag{B.9}$$

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 $\bar{a} + a_{jt} > 0$.[30] 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 $\widetilde{\mathbb{E}}_{jt}^{prior} y_{t+1} = \min_{\mu_{jt} \in [-a_{jt}, -a_{jt} + 2|a_{jt} + \bar{a}|]} \mu_{jt} = -a_{jt}$.

A 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}.[31] The firm then updates its expectations about future output growth to $\widetilde{\mathbb{E}}_{jt}^{post} y_{t+1} = -a_{jt}(1 - g_j) + g_j s_{jt}$, 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.[32] Relying on the proof of Proposition 1, one can show that the equilibrium price vector is described by

$$\boldsymbol{p}_t = \beta MC \left(G \boldsymbol{s}_t - (I - G) \boldsymbol{a}_t \right) + M_y \boldsymbol{y}_t + M_p \boldsymbol{p}_{t-1}. \tag{B.10}$$

Since every element of M is positive (see Appendix B.3.1), higher uncertainty about future output growth leads to lower current prices. Similar communication impli-

[30] Ilut and Schneider (2014) lay out the equation that is analogous to our equation (B.9) 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 (B.9). 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.

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

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

cations to the ones described in Appendix B.2 apply here, too.

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, with the assistance of survey recruitment specialists, we retained about 50 percent of the firm-pairs for the follow-up wave. These participation statistics are similar to Kumar et al. (2023)—with which we share the

same setting—despite them not requiring pairs.[33]

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

[33]Note that there is minimal overlap in the sample of firms we surveyed compared to previous research, to mitigate concerns from effects of repeated inclusion in the survey.

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.